Utilities Policy 66 (2020) 101108

Contents lists available at ScienceDirect

Utilities Policy

journal homepage: http://www.elsevier.com/locate/jup

Elasticity estimation and forecasting: An analysis of residential electricity demand in Brazil

Joilson de Assis Cabral[a,*], Maria Viviana de Freitas Cabral[b], Amaro Olímpio Pereira Júnior[c]

[a] Regional Economics and Development Programme and Management and Strategy Programme, Department of Economics, Federal Rural University of Rio de Janeiro, Institute of Applied Social Sciences, BR 465, KM 7, Seropédica, RJ, 23897-000, Brazil

[b] Regional Economics and Development Programme and Territorial Development and Public Policy Programme, Department of Economics, Federal Rural University of Rio de Janeiro, Institute of Applied Social Sciences, BR 465, KM 7, Seropédica, RJ, 23897-000, Brazil

[c] Energy Planning Programme, Federal University of Rio de Janeiro, Centro de Tecnologia, Bloco C, Sala 211, Cidade Universitária, Ilha Do Fundão, Rio de Janeiro, RJ, 21941-972, Brazil

ARTICLE INFO

Keywords:
Spatiotemporal models
Brazilian residential electricity demand
Elasticities and forecasting performance

ABSTRACT

Spatiotemporal models to estimate electricity demand are scarce in the existing literature. In this paper, we compare three models to estimate elasticities and forecast demand for residential electricity in Brazil. The Dynamic Spatial Durbin Model presented the best goodness of fit, with results that confirm the need to consider spatial dependence in the Brazilian regions. The results showed temporal inertia, inelasticity of demand concerning price and income, and a significant impact of the temperature and the number of households connected to the grid. We conclude that omitting the spatiotemporal dynamic could lead to bias in the models used by Brazilian utilities.

1. Introduction

The Brazilian Electricity Sector (BES) is a complex hydrothermal system with continental dimensions that may be considered globally unique. Its grid, called the National Interconnected Electricity System (SIN), allows for synergistic and reliable operation through regional power exchanges (Francisco, 2012), bringing reliability for the whole system. The BES has undergone two major structural reforms (in 1994 and 2004), and the current institutional model relies on three guidelines: the universalisation of supply, the security of the system and the affordability of tariffs.

Under this institutional framework, utilities must cover 100% of their markets with power purchase agreements, which are implemented through a tendering system organised by the Brazilian Electricity Regulatory Agency (ANEEL). For that, the utilities must submit each of their demand forecasts for six years ahead, so that ANEEL has the information needed to set an energy auction. To comply with this norm, the utilities need accurate demand forecasts as errors increase their operating costs (Haida and Muto, 1994). In the BES, incorrect forecasts – either 3% above or below actual demand – leads to fines for the utilities. Moreover, inaccurate forecasts also carry social and economic losses. Thus, accurate forecasts play a central and integral role in the planning and operation of utilities (Alfares and Nazeeruddin, 2002), ensuring system reliability and fair tariffs for consumers. Accurate elasticities are essential to anticipate and analyse future variations in demand as well as to plan and organise the adequately supply of electricity to the grids in their respective markets.

In other words, utilities benefit considerably from accurate elasticity estimates and forecasts for greater economic, energy and environment efficiencies when planning future contracts, with implications for minimising costs and mitigating risks. Obtaining valid estimates of elasticities and accurate demand forecasts is crucial to understanding the energy system and the impact of energy policy instruments (Boogen et al., 2017), and has substantial implications for utilities, regulators and policymakers (Feehan, 2018). Therefore, the ability to accurately model electricity demand plays a vital role in understanding, building and optimising future demand variability (Holz et al., 2020), and is arguably one of the major challenges for utilities.

Many statistical methods have been developed for forecasting and elasticities modelling. Beginning with Houthakker (1951), the development and enhancement of statistical tools has provided more precise techniques such as multiple regression (Houthakker, 1951; Anderson, 1973; Zhou and Teng, 2013), exponential smoothing (Christiaanse, 1971; El-Keib et al., 1995; Infield and Hill, 1998), Kalman filter

* Corresponding author.
E-mail addresses: cabraljoilson@gmail.com, cabraljoilson@ufrrj.br (J.A. Cabral).

https://doi.org/10.1016/j.jup.2020.101108
Received 1 April 2020; Received in revised form 8 August 2020; Accepted 8 August 2020
Available online 25 August 2020

(Moghran and Rahman, 1989; Inglesi-Lotz, 2011; Arisoy and Ozturk, 2014), Autoregressive Integrated Moving Average (ARIMA) models (Elrazaz and Mazi, 1989; Juberias et al., 1999; Cabral et al., 2017), VAR/VEC models (Modiano, 1984; Bakirtas et al., 2000; Garcez and Ghirardi, 2003; Jamil and Ahmad, 2011; Lim et al., 2014), genetic algorithm (Ma et al., 1995; Yang et al., 1996; Lee et al., 1997; Arnaout, 2017), fuzzy logic (Liang and Hsu, 1994; Ramirez-Rosado and Dominguez-Navarro, 1996; Chow and Tram, 1997; Zahedi et al., 2013; Torrini et al., 2016), neural networks (Srinivasan and Lee, 1995; Hsu and Yang, 1992; Oğcu et al., 2012; Bozkurt et al., 2017) and support vector machine (Chen et al., 2004; Tao et al., 2004; Guo et al., 2006, 2018bib_Guo_et_al_2006; Hong, 2009bib_Guo_et_al_2018). Although these models are widely used by utilities to forecast electricity demand, only parametric models can estimate elasticities. Cabral et al. (2017) pointed out that this range of models neglects the possible existence of spatial autocorrelation in electrical systems. De Siano and Sapio (2020) also highlight the importance of spatial econometrics to electricity markets.

Thus, the dynamics of the spatial data distribution can be explored to assess whether spatial autocorrelation needs to be taken into account in the specification of the econometric model, to avoid biased and inefficient estimates (Elhorst, 2010). One particular class of models that incorporates the influence of spatial interactions has recently drawn increased interest (Cabral et al., 2017; De Siano and Sapio, 2020). Nevertheless, these models fall within a time series framework, rather than in a panel data environment (Baltagi, 2008). To bridge this gap, we present a comparison of three multivariate panel data models – Dynamic Data Panel, Durbin Dynamic Spatial (Dynamic SDM), and Spatial Lag-Autoregressive Spatial Error with Autoregressive Component (SAC-AR (1)) – to assess which model is the most appropriate in yielding valid elasticities and accurate demand forecasts. Since elasticities play an important role in energy demand forecasting (Woo et al., 2018), we estimate elasticities of price, income, the number of households connected to the grid, and temperature, concerning household electricity demand.

This paper contributes to the modelling and support of electrical sector policies in at least four aspects. The first is that the comparisons of spatial multivariate panel data models which, although rare in Brazil, have aroused the interest of international researchers (Ohtsuka et al., 2010; Ohtsuka and Kakamu, 2013; Blázquez Gomez et al., 2013; Cho et al., 2015; Akarsu, 2017; De Siano and Sapio, 2020). The second is that we present a theoretical electricity demand model that considers the possible existence of spatial autocorrelation in the electrical sector. Third, the demand elasticities estimated and the forecasting performed through the studied models can be used to anticipate electricity demand variations and provide an alternative tool for better planning and expansion of energy supply to the Brazilian and international institutions in charge of the management of the electrical sector. Finally, the results of the empirical analysis suggest that there are possibilities for new research in other areas of the energy sector in which more accurate forecasts are essential, such as in streamflow, solar radiation estimates and wind forecasting.

This paper is organised in five sections, besides this introduction. The next section presents the theoretical model of residential electricity demand, taking into consideration the possible spatial autocorrelation in regional electrical systems. The third section discusses the specification of three panel models representing the electricity demand of utilities, in which the latter two consider the existence of spatial interaction within the BES. Section 4 outlines the database used, while Section 5 discusses the results. The final section rounds up the study's findings.

2. Theoretical framework for modelling residential electricity demand

The approach proposed here is based on the assumption that utilities are in a better position than anyone else to model their 'captive' markets. The rationale behind such an approach is that the responsibility for defining the level of demand to be contracted at the auctions falls to the utilities. For this, they must supply contracts to meet the total demand of their markets or face an increase in production costs if they do not.

However, the utilities have many problems in estimating demand because the information they have is usually incomplete and/or imperfect (Labandeira et al., 2012). Based on these considerations, it is necessary for the utilities to specify the electricity demand model adequately. With a well-specified demand model, utilities can model the electricity demand of their markets and ensure productive, allocative and environmental efficiencies.

Because of the limited data available to utilities, the alternative is to estimate electricity demand through aggregate data such as prices, income, the number of households connected to the grid and climatic conditions. Although there is no consensus in the literature about the most suitable functional form, most of the studies that estimate electricity demand equations adopt a linear or logarithmic form (Labandeira et al., 2012). We choose to perform an increasing monotonic transformation of the log-log type in the Cobb-Douglas demand function because the estimated coefficients are equivalent to the elasticities.

Based on Houthakker and Taylor (1970), Wilson (1971), Houthakker et al. (1974), Houthakker (1980), Modiano (1984), Filippini (1999), García-Cerruti (2000), Hondroyiannis (2004), Holtedahl and Joutz (2004), Narayan and Smyth (2005), Amarawickrama and Hunt (2008) and Arisoy and Ozturk (2014), after some algebraic rearrangements, one can specify an individual electric power demand function (D_t) for a given utility as follows:

$$\ln(D_t) = \mu + \varnothing \ln(D_{t-1}) + \beta_1 ln(P_t) + \beta_2 ln(I_t) + \beta_3 ln(U_t) + \beta_4 ln(T_t) + \varepsilon_t \quad (1)$$

where $\mu = \ln(A)$ is a constant term, D_{t-1} is the electricity demand from the previous period, P is the price of electricity, I denotes the average income of consumers, U represents the number of households connected to the grid and T is the temperature. The subscript t indicates time. Note that the prices of a possible substitute for electricity, such as natural gas or liquefied petroleum gas (LPG), are not included in Equation (1), as this would imply a change of the equipment providing the required energy service.[1]

The estimated elasticities in Equation (1) are interpreted as the direct effects of a percentage variation in a given explanatory variable on the percentage change in electricity consumption. Therefore, the estimates of β_1, β_2, β_3 and β_4 coefficients in Equation (1) can be interpreted as demand elasticities of price, income, units connected to the grid and temperature, respectively. It is expected that the price elasticity of demand (β_1) is negative, while the remaining elasticities $(\beta_2, \beta_3, \beta_4)$and the inertial demand of electricity $(\varnothing)$ should be positive. It is worth noting that the models used by the utilities have an error (ε) in their forecasts of electricity demand. Forecast errors can differentiate a cost-effective model from another that is not. These forecast errors are usually measured through the mean absolute percentage error (MAPE).

As noted by De Siano and Sapio (2020), electricity demand, in theory, is expected to be spatially dependent. However, despite the importance of the spatial spillovers on the decisions of utilities and consumers' electricity, they have been neglected for a long time. To avoid an increase in production costs resulting from inadequate models,

[1] In this paper, two goods are substitutes when the variation of the price of one good generates proportional variation in the demand of the other good, without requiring an exchange of equipment or technology to establish the substitution of one good for the other. In the current case, electricity and natural gas/LPG are not considered as substitutes since, in case of an increase in the price of electricity, for example, the increase in the demand for natural gas/LPG would only be possible through an exchange of technology. This technology exchange may not be economically viable for the consumer in the short-term.

utilities must verify if there is spatial dependence and/or heterogeneity in their markets. It is worth pointing out that Ohtsuka et al. (2010), Ohtsuka and Kakamu (2013), Blázquez Gomez et al. (2013), Cho et al. (2015), Akarsu (2017) and Cabral et al. (2017) indicated that electricity consumption is spatially dependent.

Given the above, the existing spatial dependence must be modelled on the utilities' demand function. This dependence can be modelled through the spatial lag of the electricity demand $(\boldsymbol{W}\ln(D_t))$and/or spatial spillovers $(\boldsymbol{W}\ln(X_t) where X = Wln(P_t), Wln(I_t), Wln(U_t) e Wln(T_t))$ and/or through random shocks of neighbouring regions $(\boldsymbol{W}\varepsilon_t)$. For that matter, we propose a general demand function capable of modelling spatial effects on the electricity consumption of the residential sector as specified as follows:

$$\ln(D_t) = \mu + \varnothing\ln(D_{t-1}) + \rho\boldsymbol{W}\ln(D_t) + \beta_1 ln(P_t) + \beta_2 ln(I_t) + \beta_3 ln(U_t) + \beta_4 ln(T_t) + \Psi_1 \boldsymbol{W}ln(P_t) + \Psi_2 \boldsymbol{W}ln(I_t) + \Psi_3 \boldsymbol{W}ln(U_t) + \Psi_4 \boldsymbol{W}ln(T_t) + \varepsilon_t$$

$$\varepsilon_t = \lambda\boldsymbol{W}\varepsilon_t + v_t \tag{2}$$

where ρ is the spatial autoregressive coefficient that captures the importance of existing spatial interactions (regional electricity exchanges) in the electricity consumption of the utilities. $\boldsymbol{W}$ is a spatial weights matrix. $\boldsymbol{\Psi}$measures the importance of exogenous spatial interactions. λ is the spatial autoregressive error parameter. The remainder of the notation remains the same as Equation (1).

To manage the operation and expansion of the energy system, it is necessary to propose an aggregate model capable of modelling the electricity demand for the utilities operating in the electricity sector. Simply and straightforwardly, the individual electricity power demand function can be generalised to account for an aggregate system of utilities through the summation of all utilities.

3. Methods and material

3.1. Specification of multivariate models for electricity demand in the Brazilian residential sector

In the BES, the utilities follow the Regulated Contracting Environment (RCE) guidelines. The utilities meet mainly the residential sector – the second-largest electricity market in Brazil, accounting for about 29% of the country's total supply (EPE, 2019) – and a portion of demand of the industry and services sectors. Under the framework of the RCE, the utilities are responsible for defining the level of demand to be presented at the auctions to ensure compensation for its costs in the annual tariff readjustment. Thus, the basis of the Brazilian utilities' decision-making process is related to the use of a better method to obtain valid elasticity estimates and accurate forecasts.

We specify three different models to estimate electricity demand elasticities in Brazil and compare the adjustment through the information criteria (AIC and BIC). Concerning forecast accuracy, we use MAPE because it is the most widely used measurement (Kahn, 1998; Goodwin and Lawton, 1999). Besides, as our data are positive and much greater than zero, MAPE is preferred rather than other measures of forecast error (Hyndman and Koehler, 2006). This exercise clarifies their characteristics and usage, thus contributing to research in the area.

3.1.1. Dynamic panel

A data panel is a set that includes cross-sectional data over time. As Wooldridge (2002) points out, the primary motivation for panel data use is to mitigate omitted variables bias. In the data panel structure, the central question is whether the unobserved effects are (or are not) correlated with the explanatory variables or the error term.

The Hausman (1978) test can be used to deal with unobserved effects bias in the ordinary least squares (OLS) estimates. According to the test results, either the fixed effects (FE) method or the random effects (RE) method should be employed. The FE adds a transformation to remove the unobserved effect (μ_g) from the OLS, while the RE involves a generalised least squares (GLS) estimation and should be used when the observed effect is not correlated with any of the explanatory variables.

A limitation of traditional data panel models is that they do not incorporate the possible temporal dynamics of the dependent variable. This limitation is overcome by dynamic models with panel data, which are estimated through the generalised method of moments (GMM) (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998).

Dynamic data panel models have been extensively studied in recent decades because they can capture the dynamics of the variable of interest, besides being able to control the unobservable heterogeneity among the regional units under analysis. However, they do not incorporate spatial effects, which is unfortunate because regional data often requires models that include such effects to produce consistent and efficient estimates, as both the theoretical and empirical literature emphasises.

Dynamic models for panel data are indicated when many variables of interest are related to each other and their previous values. In these cases, the GMM estimation takes into account the persistence of the dependent variable over time.

Following the above considerations, the aggregate electricity demand of utility g $(g = 1, \ldots, G)$ in period $t(t = 1, \ldots, T)$, D_{gt}, can be represented by the following log representation of a dynamic panel data model:

$$\ln(D_{gt}) = \mu_g + \varnothing\ln(D_{gt-1}) + \beta_1 ln(P_{gt}) + \beta_2 ln(I_{gt}) + \beta_3 ln(U_{gt}) + \beta_4 ln(T_{gt}) + v_{gt}$$

$$v_{gt} \sim N(0, \sigma^2) \tag{3}$$

where:

$\mu_g$is a constant term.

D_{gt-1}: aggregate electricity demand of utility g in period $t-1$,

P_{gt}: average electricity tariff charged by utility $g$in period t,

I_{gt}: average income of utility $g$consumers in period t,

U_{gt}: number of households connected to the grid in the concession area of utility g in period t,

T_t: the average temperature in the concession area of utility g in period t, and

$v_{gt}$is white noise.

If $(\varnothing + \beta_1 + \beta_2 + \beta_3 + \beta_4) < 1$, Equation (3) indicates decreasing returns to scale.[2] As noted by Varian (1992), this phenomenon occurs when at least one of the electricity demand function's explanatory factors is fixed.

Grouping the data set of the 62 utilities in the BES $(g = 1, \ldots, 62)$ in stacks, Equation (3) can be understood as the electricity demand function under a dynamic panel data structure.

As in traditional data panel models, the dynamic panel model deals with the unobserved effects inherent to each region (μ_g) through either the FE or RE method, according to the result of the Hausman test (1978). Thereafter, the GMM estimator of Arellano and Bover (1995) is used to assess the explanatory variables by computing their first differences, which are not strictly exogenous with their available lags. To handle this, Arellano and Bond (*ibid.*) propose the use of lagged variables in at least two periods$(t-2)$ as an instrument for the first difference equation to achieve consistent estimates.

3.1.2. Dynamic Spatial Durbin Model (dynamic SDM)

Integrating spatial and temporal lags in the econometric analysis of regional data is essential for building more successful models and

[2] The electricity demand function presents decreasing returns to scale when an increase in its explanatory factors implies a proportionately lower increase in electricity demand.

avoiding estimation bias (Rey and Montouri, 1999; Badinger et al., 2004). Unfortunately, the literature on temporal and spatial dynamics has progressed independently with little interaction between them (Beenstock and Felsenstein, 2007).

In the case of regional electricity demand in Brazil, we include a spatial lag of the dependent and explanatory variables because the electricity consumption of a region is probably influenced by the average consumption of electricity in neighbouring regions, as Brazilian regions are socially and economically interrelated. Furthermore, the inclusion of a spatiotemporal lag of the dependent variable in the specification of the model intends to test the hypothesis of whether inertia in the electricity demand of neighbouring regions is capable of influencing demand in the observed regional unit.

Considering the existence of spatial spillovers in Brazilian electricity demand (Cabral et al., 2017), we can specify an autoregressive spatial dynamic panel model (Debarsy et al., 2012) to represent spatial dynamics by including contemporary spatial lags of both the dependent variable and the covariates, along with time dynamics modelled by the inclusion of a temporarily lagged variable. Thus, a Dynamic Spatial Durbin Model (dynamic SDM) for the regional electricity demand in Brazil can be formalised as follows:

$$\ln(D_{gt}) = \mu_g + \varnothing ln(D_{gt-1}) + \rho_1 \boldsymbol{W_g} \ln(\boldsymbol{D}_t) + \rho_2 \boldsymbol{W_g} ln(\boldsymbol{D}_{t-1}) + \beta_1 ln(P_{gt}) + \beta_2 ln(I_{gt}) + \beta_3 ln(U_{gt}) + \beta_4 ln(T_{gt}) + \Psi_1 \boldsymbol{W_g} ln(\boldsymbol{P}_t) + \Psi_2 \boldsymbol{W_g} ln(\boldsymbol{I}_t) + \Psi_3 \boldsymbol{W_g} ln(\boldsymbol{U}_t) + \Psi_4 \boldsymbol{W_g} ln(\boldsymbol{T}_t) + v_{gt} v_{gt} \sim N(0, \sigma^2) \tag{4}$$

where:

$\boldsymbol{D}_t, \boldsymbol{D}_{t-1}, \boldsymbol{P}_t, \boldsymbol{I}_t, \boldsymbol{U}_t, \boldsymbol{T}_t are (G \times 1) vectors,$

$\varnothing$is the inertial demand of electricity.

$\rho_i, i = 1, 2$ are the spatial autoregressive coefficients that capture the importance of existing spatial interactions in$t$ and$t-1$ (electricity regional exchanges), and.

Ψ_i, $i = 1, \ldots, 4$, are parameters that measure the importance of exogenous spatial interactions.

In Equation (4), spatial dependence is modelled through a spatial weights matrix $\boldsymbol{W} = [\boldsymbol{W}_1, \ldots, \boldsymbol{W}_G]'$ where $[\ldots]'$ denotes the transpose. $\boldsymbol{W}_g$are $(1 \times G)$ vectors, so that $\boldsymbol{W}_g \ln(\boldsymbol{D}_t)$represent spatial lags of electricity demand, $\boldsymbol{W}_g ln(\boldsymbol{D}_{t-1})$ the spatiotemporal lags of electricity demand, while $\boldsymbol{W}_g ln(\boldsymbol{P}_t)$, $\boldsymbol{W}_g ln(\boldsymbol{I}_t)$, $\boldsymbol{W}_g ln(\boldsymbol{U}_t)$, and $\boldsymbol{W}_g ln(\boldsymbol{T}_t)$ denote spatial spillovers of price, income, number of households connected to the grid, and average temperature, respectively.

Once again, the unobserved effects are treated through either the FE or the RE method. To estimate the parameters of Equation (4) efficiently and consistently, the GMM proposed by Blundell and Bond (1998) was used. It should be noted that the application of a dynamic SDM to estimate electricity demand elasticities and perform forecasting in the electrical sector is original, both in Brazil and abroad.

In vector notation, Equation (4) can be written as:

$$\ln(\boldsymbol{D}_t) = \boldsymbol{\mu} + \varnothing ln(\boldsymbol{D}_{t-1}) + \rho_1 \boldsymbol{W} \ln(\boldsymbol{D}_t) + \rho_2 \boldsymbol{W} ln(\boldsymbol{D}_{t-1}) + \beta_1 ln(\boldsymbol{P}_t) + \beta_2 ln(\boldsymbol{I}_t) + \beta_3 ln(\boldsymbol{U}_t) + \beta_4 ln(\boldsymbol{T}_t) + \Psi_1 \boldsymbol{W} ln(\boldsymbol{P}_t) + \Psi_2 \boldsymbol{W} ln(\boldsymbol{I}_t) + \Psi_3 \boldsymbol{W} ln(\boldsymbol{U}_t) + \Psi_4 \boldsymbol{W} ln(\boldsymbol{T}_t) + \boldsymbol{v}_t \tag{5}$$

where: $\boldsymbol{\mu}$ and $\boldsymbol{v}_t$ are $(G \times 1)$ vectors. The rest of the notation remains the same as in Equation (4).

According to LeSage and Pace (2009), the total effects (elasticities) do not come unmistakably from the estimated coefficients. In an SDM model, to have the impact of both direct and indirect effects provided by the spatial interaction between regions of an explanatory variable, it is necessary to make the following transformation on Equation (5):

$$\ln(\boldsymbol{D}_t) - \rho_1 \boldsymbol{W} \ln(\boldsymbol{D}_t) = \boldsymbol{\mu} + \varnothing ln(\boldsymbol{D}_{t-1}) + \rho_2 \boldsymbol{W} ln(\boldsymbol{D}_{t-1}) + \beta_1 ln(\boldsymbol{P}_t) + \beta_2 ln(\boldsymbol{I}_t) + \beta_3 ln(\boldsymbol{U}_t) + \beta_4 ln(\boldsymbol{T}_t) + \Psi_1 \boldsymbol{W} ln(\boldsymbol{P}_t) + \Psi_2 \boldsymbol{W} ln(\boldsymbol{I}_t) + \Psi_3 \boldsymbol{W} ln(\boldsymbol{U}_t) + \Psi_4 \boldsymbol{W} ln(\boldsymbol{T}_t) + \boldsymbol{v}_t \tag{6}$$

Or

$$(\boldsymbol{I}_G - \rho_1 \boldsymbol{W}) \ln(\boldsymbol{D}_t) = \boldsymbol{\mu} + \varnothing ln(\boldsymbol{D}_{t-1}) + \rho_2 \boldsymbol{W} ln(\boldsymbol{D}_{t-1}) + \beta_1 ln(\boldsymbol{P}_t) + \beta_2 ln(\boldsymbol{I}_t) + \beta_3 ln(\boldsymbol{U}_t) + \beta_4 ln(\boldsymbol{T}_t) + \Psi_1 \boldsymbol{W} ln(\boldsymbol{P}_t) + \Psi_2 \boldsymbol{W} ln(\boldsymbol{I}_t) + \Psi_3 \boldsymbol{W} ln(\boldsymbol{U}_t) + \Psi_4 \boldsymbol{W} ln(\boldsymbol{T}_t) + \boldsymbol{v}_t \tag{7}$$

where $\boldsymbol{I}_G$ is a $(G \times G)$ identity matrix. After pre-multiplying both sides of Equation (7) by $(\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1}$ and rearranging the terms of the right side, we reach:

$$\ln(\boldsymbol{D}_t) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} \boldsymbol{\mu} + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\varnothing \boldsymbol{I}_G + \rho_2 \boldsymbol{W}) ln(\boldsymbol{D}_{t-1}) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_1 \boldsymbol{I}_G + \Psi_1 \boldsymbol{W}) ln(\boldsymbol{P}_t) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_2 \boldsymbol{I}_G + \Psi_2 \boldsymbol{W}) ln(\boldsymbol{I}_t) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_3 \boldsymbol{I}_G + \Psi_3 \boldsymbol{W}) ln(\boldsymbol{U}_t) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_4 \boldsymbol{I}_G + \Psi_4 \boldsymbol{W}) ln(\boldsymbol{T}_t) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} \boldsymbol{v}_t \tag{8}$$

As discussed by Elhorst (2010), the interpretation of the results of the dynamic SDM model in Equation (8) needs to take into account the fact that it contains temporally lagged, spatially lagged, besides temporally and spatially lagged dependent and independent variables. To help with this interpretation, we use the following notation (LeSage and Pace, 2009, p. 114):

$$S_\mu(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} \boldsymbol{\mu} \tag{9}$$

$$S_D(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\varnothing \boldsymbol{I}_G + \rho_2 \boldsymbol{W}) \tag{10}$$

$$S_P(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_1 \boldsymbol{I}_G + \Psi_1 \boldsymbol{W}) \tag{11}$$

$$S_I(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_2 \boldsymbol{I}_G + \Psi_2 \boldsymbol{W}) \tag{12}$$

$$S_U(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_3 \boldsymbol{I}_G + \Psi_3 \boldsymbol{W}) \tag{13}$$

$$S_T(\boldsymbol{W}) = (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} (\beta_4 \boldsymbol{I}_G + \Psi_4 \boldsymbol{W}) \tag{14}$$

Equation (8) can thus be written as

$$\ln(\boldsymbol{D}_t) = S_\mu(\boldsymbol{W}) + S_D(\boldsymbol{W}) ln(\boldsymbol{D}_{t-1}) + S_P(\boldsymbol{W}) ln(\boldsymbol{P}_t) + S_I(\boldsymbol{W}) ln(\boldsymbol{I}_t) + S_U(\boldsymbol{W}) ln(\boldsymbol{U}_t) + S_T(\boldsymbol{W}) ln(\boldsymbol{T}_t) + (\boldsymbol{I}_G - \boldsymbol{W}\rho_1)^{-1} \boldsymbol{v}_t \tag{15}$$

According to LeSage and Pace (ibid.), the empirical results of the dynamic SDM model, in particular demand elasticities, can be summarised as direct, indirect and total effects by:

$$\overline{E}(r)_{direct} = G^{-1} tr(S_r(\boldsymbol{W})) \tag{16}$$

$$\overline{E}(r)_{total} = G^{-1} \iota_G' S_r(\boldsymbol{W}) \iota_G \tag{17}$$

$$\overline{E}(r)_{indirect} = \overline{E}(r)_{total} - \overline{E}(r)_{direct} \tag{18}$$

where tr denotes the trace, ι_G an $(G \times 1)$ vector of ones and. $r = \mu, D, P, I, U, T$.

In the studied case, the $\overline{E}(r)_{direct}$ can be understood as the change in the electricity demand of region g due to a change of variable r in the same region, $\overline{E}(r)_{indirect}$ as the change on the electricity demand of region g due to a change of variable $r$in neighbouring regions and $\overline{E}(r)_{total}$ as the change in the electricity demand of region g due to a change of variable r in the same region plus the effect of neighbouring regions, which exert a feedback effect on the electricity demand of region g, i.e., this refers to elasticities in the dynamic SDM model.

3.1.3. Spatial lag model and autoregressive spatial error with autoregressive components (SAC-AR(1))

When patterns of electricity consumption in neighbouring regions are correlated with local consumption and unobserved variables are spatially correlated, the SAC model is appropriate to deal with these spatial effects. This is because the SAC combines both spatial lag and autoregressive spatial error, thus taking into account spatial spillovers both in the endogenous variable and in the error term.

Furthermore, as indicated in Equation (1), it is plausible to assume that the current electricity consumption carries an inertial component from the previous period, which is why a temporal autoregressive component is included in the so-called SAC-AR(1) model (Cho et al., 2015), as shown in Equation (19) below.

$$\ln(D_{gt}) = \mu_g + \varnothing\, ln(D_{gt-1}) + \rho_1 \boldsymbol{W}_g \ln(\boldsymbol{D}_t) + \beta_1 ln(P_{gt}) + \beta_2 ln(I_{gt}) + \beta_3 ln(U_{gt}) + \beta_4 ln(T_{gt}) + \varepsilon_{gt}$$

$$\varepsilon_{gt} = \lambda \boldsymbol{W}_g \boldsymbol{\varepsilon}_t + v_{gt} \tag{19}$$

where $\boldsymbol{\varepsilon}_t$ is a $(G \times 1)$vector of spatially lagged errors and $\lambda(|\lambda| < 1)$ is the spatial autoregressive coefficient of the residues. The remainder of the notation is the same as in Equation (1). Maintaining the same notation as before, Equation (19) can be written in vector form as:

$$\ln(\boldsymbol{D}_t) = \boldsymbol{\mu} + \varnothing\, ln(\boldsymbol{D}_{t-1}) + \rho_1 \boldsymbol{W} \ln(\boldsymbol{D}_t) + \beta_1 ln(\boldsymbol{P}_t) + \beta_2 ln(\boldsymbol{I}_t) + \beta_3 ln(\boldsymbol{U}_t) + \beta_4 ln(\boldsymbol{T}_t) + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\varepsilon}_t = \lambda \boldsymbol{W} \boldsymbol{\varepsilon}_t + \boldsymbol{v}_t \tag{20}$$

Analogous to the models specified by Equations (3)–(5), the unobserved heterogeneity for utility g (μ_g) was treated through either the FE or the RE method. The maximum likelihood (ML) method, as proposed by Elhorst (2010) and Lee and Yu (2010), was used to estimate the SAC-AR (1) spatial data panel specified in Equation (20). The choice of the ML estimation rests on its simplicity in dealing with the endogeneity of the $\boldsymbol{W} \ln(\boldsymbol{D}_t)$ variable, besides being a widely accepted method.

It is worth noting that the elasticities of the SAC-AR (1) model must be calculated through a similar transformation to dynamic SDM elasticities, following Equations (6)–(18).

3.2. Database

The database used consists of monthly panel data from January 2008 to December 2018 for the five Brazilian regions of the National Interconnected Electricity System: North, Northeast, Central-West, Southeast and South. Because of limitations in the available data, we are not estimating the demand for a particular utility, but rather for an 'equivalent utility' in a given region, i.e. an aggregation of the utilities in that region. The panel contains 132 observations for each region, totalling 660 observations.

The data for electricity demand, the number of households connected to the grid and tariffs were obtained through the Decision Support System (SAD) of the ANEEL. The proxy to average per capita regional income was computed by dividing aggregate monthly regional wages by the total number of workers in the region. The former was extracted from the General Cadastre for Employed and Unemployed (CAGED), while the latter was gathered by combining the data from CAGED with that of the Annual Social Information Report (RAIS). The data on the average temperatures of regions were taken from the Meteorological Database for Teaching and Research of the Brazilian Institute of Meteorology (BDMEP/INMET). The series of electricity demand was seasonally adjusted, while data of price and income were deflated. Table 1 summarises the sources and units of the data used in the estimation of the three proposed models.

Table 1
Summary of data sets used.

Variable	Description	Unit	Source
D_g	Aggregate Electricity Demand in Region g	GWh	SAD/ANEEL
P_g	Average Electricity Tariff in Region g	R$	SAD/ANEEL
I_g	Average Per Capita Income in Region g	R$	CAGED/ RAIS/MT
U_g	Number of Households Connected to the Grid in Region g	Quantity	SAD/ANEEL
T_g	Average Temperature in Region g	^{o}C	BDMEP/ INMET

4. Results and discussion

4.1. Empirical results

As mentioned before, the Hausman test was performed to deal with the unobserved effects inherent to each region (μ_g) in the proposed data panel models. The result of the test rejected the null hypothesis that the RE method would be consistent, thus indicating that the FE method is more appropriate, i.e., μ_g is constant. Therefore, all three models were estimated with the correction of unobserved effects through the FE method.

The lagged dependent variable on the right side of the models' equations acts as an endogenous regressor. To address this temporal endogeneity in the estimation of the dynamic panel model, we employed the Blundell and Bond (1998) estimator, which is an extension of the estimator developed by Arellano and Bond (1991). It consists of taking the first differences in Equation (3) and estimating its parameters through GMM. With this method, specific unobserved time-invariant effects are removed.

Furthermore, it is necessary to verify the coefficients' consistency by applying the Arellano-Bond autocorrelation test, which is performed on the residuals in difference. The hypothesis to be tested is whether there is a serial correlation of first and second orders, with it being desirable to reject the second but not the first. The reason for this is that if there is no second-order serial correlation in the residuals in the first difference, i.e. $E(\Delta v_{g,t}\Delta v_{g,t-2}) = 0$, then there is no serial autocorrelation in the residuals at this level as assumed by the Blundell and Bond method. In the studied case, the values of the Arellano-Bond autocorrelation test for the first and second orders were -2.138^{**} and -0.461, respectively, which implies that the estimates are consistent since it is possible to reject the null hypothesis of the absence of second-order serial correlation.

It is also necessary to test whether the residuals of the dynamic panel are spatially autocorrelated because either spatial autoregressive errors would make the estimates inefficient or spatial lags in the dependent variable and/or spatial spillovers of exogenous variables would imply biased estimates. The CD-Pesaran test (6.60***) showed that there is *cross-sectional* spatial dependence between regions, which was confirmed by the Moran's I test spatial autocorrelation statistic (0.257***) indicating the existence of spatial dependence on residuals at the 1% level of significance. As suggested by De Siano and Sapio (2020), electricity demand is expected to be spatially dependent because, besides resources and production, consumption of energy also is defined over time and space. Despite the existing spatial nature in the electricity sector, spatial dependence has been neglected in electricity sector modelling.

Table 2 below shows the results of the three estimated models: Dynamic Panel, Dynamic SDM and SAC-AR(1). The results show that the dynamic SDM model has the best goodness of fit to estimate the elasticities since it presented the lowest AIC and BIC information criteria. Besides, the model's lowest MAPE confirms that the spatiotemporal dynamic SDM model is the most adequate to predict regional electricity demand in Brazil. Therefore, the spatiotemporal dimension must be incorporated into the models used by the electricity sector.

As previously mentioned, the estimated coefficients of the dynamic SDM model displayed in Table 2 cannot be directly interpreted as elasticities. To find them, it is necessary to perform the transformation proposed by LeSage and Pace (2009), detailed in subsection 3.2. The results of this transformation are displayed in Table 3.

Table 2
Results for estimation of the proposed models.

Demand: $ln(D_{gt})$	Dynamic Panel	Dynamic SDM	SAC-AR(1)
$\widehat{\varnothing}$	0.889***	0.713***	0.731***
	(0.012)	(0.023)	(0.024)
$\widehat{\beta}_1$	−0.078***	−0.152***	−0.166***
	(0.014)	(0.026)	(0.030)
$\widehat{\beta}_2$	0.030***	0.055***	0.097***
	(0.005)	(0.021)	(0.025)
$\widehat{\beta}_3$	0.106***	0.39***	0.44***
	(0.013)	(0.046)	(0.045)
$\widehat{\beta}_4$	0.016**	0.037***	0.059***
	(0.008)	(0.010)	(0.001)
$\widehat{\Psi}_1$		0.058***	
		(0.015)	
$\widehat{\Psi}_2$		−0.024*	
		(0.013)	
$\widehat{\Psi}_3$		−0.100***	
		(0.036)	
$\widehat{\Psi}_4$		0.011	
		(0.007)	
$\widehat{\rho}_1$		0.242***	0.014
		(0.024)	(0.043)
$\widehat{\rho}_2$		−0.185***	
		(0.023)	
$\widehat{\lambda}$			−0.206***
			(0.056)
Constant	0.084**	−0.221	—
	(0.042)	(0.295)	
AIC[a]	−3.497	−3.710	−2.969
BIC[b]	−3.489	−3.693	−2.959
MAPE	0.193	0.147	0.374
Number of observations	660	660	660

Notes: Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.
[a] Akaike Information Criterion.
[b] Bayesian Information Criterion.

4.2. Discussion

This paper used monthly panel data from January 2008 to December 2018 of the 'equivalent utilities' to model regional electricity demand in the Brazilian household sector. Our findings in terms of forecast accuracy improvements by spatial models are similar to those found in Ohtsuka et al. (2010), who studied Japanese utilities. In the Brazilian case, Cabral et al. (2017) confirmed the predictive performance superiority of the space-time model (ARIMASp) to predict the electricity demand of the 'Southeast Equivalent Utility' in a univariate context. Additionally, along the same lines as the findings of our paper, Ohtsuka and Kakamu (2013), Blázquez Gomez et al. (2013), Noonan et al. (2013), Cho et al. (2015) and Akarsu (2017) found evidence that spatial models are more suitable for estimating elasticities of residential electricity demand in Spanish provinces, the Greater Chicago area/USA, South Korean regions and Turkish provinces, respectively.

As seen in Table 3, the total effect of the temporal inertia of electricity consumption in Brazilian regions is 0.697, which suggests that the temporal inertia of regional consumption is relevant in explaining current consumption. This result reveals that electricity consumption habits are relatively stable in Brazilian residences; after all, electricity is an essential good.

Table 3
Summary of estimated regional electricity demand elasticities in Brazil – Dynamic SDM model.

r	$\overline{E}(r)_{direct}$	$\overline{E}(r)_{indirect}$	$\overline{E}(r)_{total}$
D	0.941	−0.244	0.697
P	−0.201	0.077	−0.124
I	0.073	−0.032	0.041
U	0.515	−0.132	0.383
T	0.049	0.015	0.063

Electricity prices can vary stochastically across time and space (Bohn et al., 1984). According to our data, the price elasticity of demand is −0.124, which means that a 1% tariff increase would decrease consumption by 0.124%. This price inelasticity arises from a lack of substitute goods and alternatives to electricity in Brazilian residences, suggesting that a policy to reduce consumption by tariff increases alone would not be effective. The tariff flags system, which was introduced in 2015 to compensate for higher generation costs due to the greater use of thermal rather than hydro plants, has thus had a limited impact. A similar situation occurs with wages, which are quite inelastic, i.e., an increase in income will give rise, ceteris paribus, to a less-than proportional increase in electricity demand. From the microeconomic view, this result shows that electricity is a necessary good for Brazilian households. We observe that electricity demand is responsive to income level, with an elasticity of 0.041.

The demand inelasticity in relation to price and income found here are in line with those found in previous studies about the BES (Modiano, 1984; Andrade and Lobão, 1997; Schmidt and Lima, 2004; Rodrigues et al., 2013; Uhr et al., 2019). Internationally, most studies about electricity demand elasticities have also found that demand is inelastic in relation to price and income (for example, see Anderson, 1973; Houthakker et al., 1974; Filippini, 1999; Labandeira et al., 2012; Blázquez Gomez et al., 2013; Akarsu, 2017). We highlight that the different economic conditions in the countries lead to different household responses to changes in electricity prices and incomes. Developing economies have income and price elasticities larger than developed countries. Households in developing countries are more sensitive to changes in electricity price and wages, indicating that as the economy grows, the electricity demand is gradually satisfied, which leads to the reduction in the income and price elasticities (Zhu et al., 2018). Therefore, the results found in our estimations are consistent with the results of Brazilian and international surveys.

As expected, the number of residences connected to the grid has a higher demand elasticity (0.383). This finding means that for every 1% additional residences connected to the grid, electricity consumption increases by 0.383%. This result is interesting as it allows utilities to improve the quality of electricity supply, plan the expansion of their grid as well as anticipate variations in electricity demand due to universalisation programmes – such as 'Light for All' – that aim to provide access to electricity to all Brazilian households. It also suggests that programmes to encourage the regularisation of consumption – like the 'Social Tariff' – can be tools to reduce the electricity theft that is quite commonplace in poorer neighbourhoods.

Given the continental dimension and the tropical climate of Brazil, the ambient temperature varies widely among regions. With this, we understand that temperature is a key driver of electricity demand variation in the BES. Despite this, few consider the influence of temperature on electricity demand in Brazil, and only Depaula and Mendelsohn (2010), Hollanda et al. (2012) and Rodrigues et al. (2013) incorporated the climate as an explanatory factor for residential electricity demand. As Table 3 shows, there is a positive relationship between electricity demand and average temperature, with an elasticity of 0.063. The weather affects the behaviour of Brazilian households by reducing the margin of reaction to variation in electricity demand. The energy services are relatively stable, i.e., the consumers use equipment throughout the year to guarantee indoor thermal comfort. This habit implies low elasticity of demand with respect to temperature.

The spatial lags $(\widehat{\rho}_1, \widehat{\rho}_2)$ and spillovers of the explanatory variables $(\widehat{\Psi}_1, \widehat{\Psi}_2, \widehat{\Psi}_3, \widehat{\Psi}_4)$were statistically significant, meaning that a particular policy related to price, income, residences connected to the grid and temperature in a given region aiming at varying electricity demand will affect not only that region but also the neighbouring regions. For example, a pricing policy that leads to an increase of 1% in electricity tariffs of utilities in the neighbouring regions would increase the electricity consumption in the analysed utility by 0.058%. Moreover, every additional 1% in the electricity demand of utilities in the neighbouring regions increases the electricity consumption of the utility by 0.242%.

This spatial dependence in household consumption is due to the interdependence of socioeconomic activities, similar lifestyle trends and consumption behaviours, as well as migration flows among Brazilian regions. Spatial spillovers of regional economic factors should be considered in the models used by utilities, regulators, and policymakers in the BES to estimate elasticities and forecast demand.

5. Conclusions

This paper provided a comparison of three panel data models that have shown the importance of considering spatial interactions to modelling electricity demand for the Brazilian household sector. The dynamic SDM model obtained the best goodness of fit to estimate the elasticities and forecast electricity demand. Thus, we conclude that omitting spatiotemporal dynamic leads to bias in the models used by the Brazilian utilities. The bias in the estimated parameters generates waste of energy and environmental resources besides increasing the probability of blackouts, which in turn decreases the profit of the utilities. Hence, valid demand elasticity estimation and accurate demand forecasting are major objectives in utility decision-making. The dynamic SDM model established here could be efficiently used to define the electricity demand to be contracted in energy auctions and be used in the annual tariff adjustment, while helping the utilities to make investment and planning decisions.

The model estimated the elasticities with respect to tariff, income, number of households connected to the grid and temperature. The results showed that price and income are inelastic, in line with the findings of international and local literature. We verified significant temporal inertia and the substantial impact of the number of residences connected to the grid on overall household electricity demand. On the other hand, the elasticity of the regional average temperature was minimal.

The penetration over time and space of intermittent renewable energy and systems of distributed generation – which allow customers to invest in small power plants for their own consumption – will promote geographic de-concentration in the BES. As a result, spatial econometrics models will gain importance in modelling the electricity markets and will be paramount to achieving the BES goals of security of electricity supply, affordability of tariffs and universalisation of access.

Finally, the models presented in this paper could be particularly useful in other areas of the BES. They could be employed, for example, to improve the accuracy of streamflow forecasts, which are of enormous importance to the supply of energy in Brazil given the country's hydropower resources, as well as in wind and solar power modelling and prediction.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Professor Luiz Fernando Legey for their comments in the preliminary version of this paper. The authors also acknowledge the referees for very helpful comments and suggestions that have greatly improved the paper. The authors also thank CAPES, CNPq, and FAPERJ for financial support.

References

Akarsu, G., 2017. Analysis of regional electricity demand for Turkey, Regional Studies. Regional Science 4 (1), 32–41. https://doi.org/10.1080/21681376.2017.1286231.

Alfares, H.K., Nazeeruddin, M., 2002. Electric load forecasting: literature survey and classification of methods. Int. J. Syst. Sci. v. 33 (number 1), 23–34.

Amarawickrama, H.A., Hunt, L.C., 2008. Electricity demand for Sri Lanka: a time series analysis. Energy 33 (5), 724–739. https://doi.org/10.1016/j.energy.2007.12.008.

Anderson, K.P., 1973. Residential energy use: an econometric analysis. In: The Rand Corporation. EUA, Santa Monica, California.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58 (2), 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econom. 68 (1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D.

Arisoy, I., Ozturk, I., 2014. Estimating industrial and residential electricity demand in Turkey: a time varying parameter approach. Energy 66 (1), 959–964. https://doi.org/10.1016/j.energy.2014.01.016.

Arnaout, J.P., 2017. Forecasting Kuwait's electricity consumption using genetic algorithms. J. Energy Dev. 42, 223–237.

Badinger, H., Müller, W.G., Tondl, G., 2004. Regional convergence in the European Union 1985-1999: a spatial dynamic panel analysis. Reg. Stud. v. 38 (3), 241–253. https://doi.org/10.1080/003434042000211105.

Bakirtas, T., Karbuz, S., Bildirici, M., 2000. An econometric analysis of electricity demand in Turkey. METU Stud. Dev. 27 (1–2), 23–34. Ankara Turkey, 2000.

Baltagi, B.H., 2008. Forecasting with panel data. J. Forecast. 27 (2), 153–173. https://doi.org/10.1002/for.1047.

Beenstock, M., Felsenstein, D., 2007. Spatial vector autoregressions. Spatial Econ. Anal. 2 (2), 167–196. https://doi.org/10.1080/17421770701346689.

Blázquez Gomez, L.M., Filippini, M., Heimsch, F., 2013. Regional impact of changes in disposable income on Spanish electricity demand: a spatial econometric analysis. Energy Econ. 40 (Suppl. 1), S58–S66. https://doi.org/10.1016/j.eneco.2013.09.008.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87 (1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8.

Bohn, R., Caramanis, M., Schweppe, R., 1984. Optimal pricing in electrical networks over space and time. Rand J. Econ. 15 (3), 360–376.

Boogen, N., Datta, S., Filippini, M., 2017. Dynamic models of residential electricity demand: evidence from Switzerland. Energy Strategy Reviews v. 18, 85–92. https://doi.org/10.1016/j.esr.2017.09.010.

Bozkut, Ö.Ö., Biricik, G., Tayşi, Z.C., 2017. Artificial neural network and SARIMA based models for power load forecasting in Turkish electricity market. PloS One 12 (4), 1–24. https://doi.org/10.1371/journal.pone.0175915.

Cabral, J.A., Legey, L.F.L., Cabral, M.V.F., 2017. Electricity consumption forecasting in Brazil: a spatial econometrics approach. Energy 126 (1), 124–131. https://doi.org/10.1016/j.energy.2017.03.005.

Chen, N., Wencong, L., Yang, J., Li, G., 2004. Support Vector Machine in Chemistry, 1 ed. World Scientific Publishing Company, Singapura.

Cho, S.-H., Taeyoung, K., Hyun, J.K., Kihyun, P., Roland, K.R., 2015. Regionally-varying and regionally-uniform electricity pricing policies compared across four usage categories. Energy Econ. v. 49, 182–191. https://doi.org/10.1016/j.eneco.2015.02.009.

Chow, M., Tram, H., 1997. Application of fuzzy logic technology for spatial load forecasting. IEEE Trans. Power Syst. 12, 1360–1366. https://doi.org/10.1109/TDC.1996.547580.

Christiaanse, W.R., 1971. Short-term load forecasting using general exponential smoothing. IEEE Trans. Power Apparatus Syst. 90 (2), 900–902. https://doi.org/10.1109/TPAS.1971.293123.

Debarsy, N., Ertur, C., Lesage, J.P., 2012. Interpreting dynamic space-time panel data models. Stat. Methodol. v.9 (1–2), 158–171. https://doi.org/10.1016/j.stamet.2011.02.002.

Depaula, G., Mendelsohn, R.O., 2010. Development and the impact of climate change on energy demand: evidence from Brazil. Climate Change Economics (CCE) v. 01 (number 3), 187–208. https://doi.org/10.1142/S2010007810000157.

De Siano, R., Sapio, A., 2020. Spatial Econometrics in Electricity Markets Research. World Scientific Book Chapters, pp. 121–156. https://doi.org/10.1142/9789813278387_0006.

Elhorst, J.P., 2010. Spatial Econometrics from Cross-Sectional Data to Spatial Panels. Springer Briefs in Regional Science, Heidelberg.

El-Keib, A.A., Ma, X., Ma, H., 1995. Advancement of statistical based modeling for short-term load forecasting. Elec. Power Syst. Res. 35 (1), 51–58. https://doi.org/10.1016/0378-7796(95)00987-6.

Elrazaz, Z.S., Mazi, A.A., 1989. Unified weekly peak load forecasting for fast growing power system. IEE Proceedings C - Generation, Transmission and Distribution 136 (1), 29–34. https://doi.org/10.1049/ip-c.1989.0005.

EPE (Empresa de Pesquisa Energética), 2019. Anuário Estatístico de Energia Elétrica. Ministério de Minas e Energia, Rio de Janeiro.

Feehan, J.P., 2018. The long-run price elasticity of residential demand for electricity: results from a natural experiment. Util. Pol. 51, 12–17. https://doi.org/10.1016/j.jup.2018.02.003.

Filippini, M., 1999. Swiss residential demand for electricity. Appl. Econ. Lett. 6 (8), 533–538. https://doi.org/10.1080/135048599352880.

Francisco, C.M., 2012. Connecting Renewable Power Plant to the Brazilian Transmission Power System. The institute of Brazilian business and public management issues, The Minerva program, Washington, DC, USA.

Garcez, E.W., Ghirardi, A.G., 2003. Proceedings of the 31st Brazilian Economics Meeting from ANPEC - Brazilian Association of Graduate Programs in Economics, 2003.
Goodwin, P., Lawton, R., 1999. On the asymmetry of the symmetric MAPE. Int. J. Forecast. v. 15, 405–408. https://doi.org/10.1016/S0169-2070(99)00007-2.
Guo, L., Chen, J., Wu, F., Wang, M., 2018. An electric power generation forecasting method using support vector machine. Systems Science & Control Engineering 6 (3), 191–199. https://doi.org/10.1080/21642583.2018.1544947.
Guo, Y.C., Niu, D.X., Chen, Y.X., 2006. Support vector machine model in electricity load forecasting. Proceedings of the Fifth International Conference on Machine Learning and Cybernetics, Dalian 13–16. August 2006.
Haida, T., Muto, S., 1994. Regression based peak load forecasting using a transformation technique. IEEE Trans. Power Syst. 9, 1788–1794. https://doi.org/10.1109/59.331433.
Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1272.
Hollanda, L., Dias, V.P., Saraiva, J.D., 2012. Essays on Economic Regulation: Chapter 2 – A Microdata Approach to Household Electricity Demand in Brazil Rio de Janeiro. Graduate School of Economics, Getulio Vargas Foundation (EPGE) (Doctoral thesis).
Holtedahl, P., Joutz, F.L., 2004. Residential electricity demand in Taiwan. Energy Econ. 26, 201–224. https://doi.org/10.1016/j.eneco.2003.11.001.
Holz, F., Karakosta, C., Neumann, A., 2020. The challenges of spatial and temporal aggregation: modelling issues, applications, and policy implications. Util. Pol. 62, 100993. https://doi.org/10.1016/j.jup.2019.100993.
Hondroyiannis, G., 2004. Estimating residential demand for electricity in Greece. Energy Econ. 26, 319–334. https://doi.org/10.1016/j.eneco.2004.04.001.
Hong, W.-C., 2009. Electric load forecasting by support vector model. Appl. Math. Model. 33, 2444–2454. https://doi.org/10.1016/j.apm.2008.07.010.
Houthakker, H.S., 1951. Some calculations of electricity consumption in Great Britain. J. Roy. Stat. Soc. v. 114 (number 3), 359–371.
Houthakker, H.S., 1980. Residential electricity revisited. Energy J. 1 (1), 29–41.
Houthakker, H.S., Taylor, L.D., 1970. Consumer Demand in the United States 1929-1970, Analysis and Projections, 2ed. Harvard University Press.
Houthakker, H.S., Verleger, P.K., Sheehan, D.P., 1974. Dynamic demand analyses for gasoline and residential electricity. Am. J. Agric. Econ. 56, 412–418.
Hsu, Y.Y., Yang, L.C., 1992. Design of artificial neural networks for short term load forecasting. IEEE Proceedings 138, 407–413.
Hyndman, R.J., Koehler, A.B., 2006. Another look at measures of forecast accuracy. International Journal of Forecasting, Elsevier vol. 22 (4), 679–688.
Infield, D.G., Hill, D.C., 1998. Optimal smoothing for trend removal in short term electricity demand forecasting. IEEE Trans. Power Syst. 13 (3), 1115–1120. https://doi.org/10.1109/59.709108.
Inglesi-Lotz, R., 2011. The evolution of price elasticity of electricity demand in South Africa: a Kalman filter application. Energy Pol. 39, 3690–3696. https://doi.org/10.1016/j.enpol.2011.03.078.
Jamil, F., Ahmad, E., 2011. Income and price elasticities of electricity demand: aggregate and sector-wise analyses. Energy Pol. 39 (9), 5519–5527. https://doi.org/10.1016/j.enpol.2011.05.010.
Juberias, G., Yunta, R., Garcia Morino, J., 1999. A new ARIMA model for hourly load forecasting. IEEE Transmission and Distribution Conference Proceedings 1, 314–319. https://doi.org/10.1109/TDC.1999.755371.
Kahn, K.B., 1998. Benchmarking sales forecasting performance measures. J. Bus. Forecast. Methods Syst. v.17 (4), 19–23 winter 1998/1999.
Labandeira, X., Labeaga, J.M., Lopez-Otero, X., 2012. Estimation of elasticity price of electricity with incomplete information. Energy Econ. 34 (3), 627–633. https://doi.org/10.1016/j.eneco.2011.03.008.
Lee, L.F., Yu, J., 2010. Some recent developments in spatial panel data models. Reg. Sci. Urban Econ. 40 (5), 255–271. https://doi.org/10.1016/j.regsciurbeco.2009.09.002.
Lee, D.G., Lee, B.W., Chang, S.H., 1997. Genetic programming model for long-term forecasting of electric power demand. Elec. Power Syst. Res. 40 (1), 17–22. https://doi.org/10.1016/S0378-7796(96)01125-X.
LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton.
Liang, R.H., Hsu, Y.Y., 1994. Fuzzy linear programming: an application to hydroelectric generation scheduling. IEE Proc. Generat. Transm. Distrib. 141 (6), 568–574. https://doi.org/10.1049/ip-gtd:19941357.
Lim, K.-M., Lim, S.-Y., Yoo, S.-H., 2014. Short- and long-run elasticities of electricity demand in the Korean service sector. Energy Pol. 67, 517–521. https://doi.org/10.1016/j.enpol.2013.12.017.
Ma, X., El-Keib, A.A., Smith, R.E., Ma, H., 1995. Genetic algorithm based approach to thermal unit commitment of electric power systems. Elec. Power Syst. Res. 34, 29–36. https://doi.org/10.1016/0378-7796(95)00954-G.
Modiano, E.M., 1984. Income Elasticity of Electricity Demand Prices in Brazil. PUC Economics Department, Rio de Janeiro (Discussion text n. 68).
Moghram, I., Rahman, S., 1989. Analysis and evaluation of five short-term load forecasting techniques. IEEE Trans. Power Syst. 4 (4), 1484–1491. https://doi.org/10.1109/59.41700.
Narayan, P.K., Smyth, R., 2005. The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration. Energy Pol. 33 (4), 467–474. https://doi.org/10.1016/j.enpol.2003.08.011.
Oğcu, G., Omer, F.D., Selim, Z., 2012. Forecasting electricity consumption with neural networks and support vector regression. Procedia - Social and Behavioral Sciences 58, 1576–1585. https://doi.org/10.1016/j.sbspro.2012.09.1144.
Ohtsuka, Y., Kakamu, K., 2013. Space-time model versus VAR model: forecasting electricity demand in Japan. J. Forecast. 32, 75–85. https://doi.org/10.1002/for.1255.
Ohtsuka, Y., Oga, T., Kakamu, K., 2010. Forecasting electricity demand in Japan: a Bayesian spatial autoregressive ARMA approach. Comput. Stat. Data Anal. 54 (11), 2721–2735. https://doi.org/10.1016/j.csda.2009.06.002.
Ramirez-Rosado, I.J., Dominguez-Navarro, J.A., 1996. Distribution planning of electric energy using fuzzy models. Int. J. Power Energy Syst. 16, 49–55.
Rey, S.J., Montouri, B.D., 1999. US regional income convergence: a spatial econometric perspective. Reg. Stud. 33 (2), 143–156. https://doi.org/10.1080/00343409950122945.
Rodrigues, L.A., Feres, J.G., Mattos, L.B., 2013. Global warming and the residential demand of electricity in Brazil. In: 41 National Meeting of Economics Organized by the ANPEC, 2013, Foz Do Iguaçu. Foz 41 ANPEC, 2013. vol. 41.
Srinivasan, D., And Lee, M. A. (1995). Survey of hybrid fuzzy neural approaches to electric load forecasting. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Part 5, Vancouver, BC, 4004-4008.
Tao, X., Renmu, H., Peng, W., 2004. Input dimension reduction for load forecasting based on support vector machines. In: Proc. IEEE Int. Conf. Elect. Utility Deregulation, Restruct. Power Tech, pp. 510–514. Hong Kong.
Torrini, F.C., Souza, R.C., Cyrino Oliveira, F.L., Moreira Pessanha, J.F., 2016. Long term electricity consumption forecast in Brazil: a fuzzy logic approach. Soc. Econ. Plann. Sci. 54, 18–27. https://doi.org/10.1016/j.seps.2015.12.002.
Uhr, D.A.P., Chagas, A.L.S., Uhr, J.G.Z., 2019. Estimation of elasticities for electricity demand in Brazilian households and policy implications. Energy Pol. 129, 69–79. https://doi.org/10.1016/j.enpol.2019.01.061.
Varian, H.R., 1992. Microeconomic Analysis. W&W Norton & Co, New York.
Wilson, J.W., 1971. Residential demand for electricity. Q. Rev. Econ. Bus. 11 (1), 7–12.
Woo, C.K., Liua, Y., Zarnikaub, J., Shiuc, A., Luoa, X., Kahrl, F., 2018. Price elasticities of retail energy demands in the United States: new evidence from a panel of monthly data for 2001–2016. Appl. Energy 222, 460–474. https://doi.org/10.1016/j.apenergy.2018.03.113.
Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data, first ed. MIT Press.
Yang, H.T., Huang, C.M., Huang, C.L., 1996. Identification of ARMAX model for short term load forecasting: an evolutionary programming approach. IEEE Trans. Power Syst. 11 (1), 403–408. https://doi.org/10.1109/59.486125.
Zahedi, G., Azizi, S., Bahadori, A., Alkamel, A., Wan Sr., Alwi, 2013. Electricity demand estimation using an adaptive neuro-fuzzy network: a case study from the Ontario province e Canada. Energy 49 (1), 323–328. https://doi.org/10.1016/j.energy.2012.10.019.
Zhou, S., Teng, F., 2013. Estimation of urban residential electricity demand in China using household survey data. Energy Pol. 61, 394–402. https://doi.org/10.1016/j.enpol.2013.06.092.
Zhu, X., Li, L., Zhou, K., Zhang, X., Yang, S., 2018. A meta-analysis on the price elasticity and income elasticity of residential electricity demand. J. Clean. Prod. 201, 169–177. https://doi.org/10.1016/j.jclepro.2018.08.027.