USING VEC FORMULATION FOR ENERGY DEMAND AND CONSUMPTION FORECASTS FOR SHORT AND LONG TERM CONSIDERING THE IMPACT OF PRICE-ELASTICITY AND EXTERNAL SHOCKS

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ABSTRACT

The paper presents the models that were developed to make forecasts for demand and electricity consumption for the horizons from 1 to 6 months (short term) and from 1 to 5 years (long term). In order to grasp the uncertainties mentioned above, it aims at measuring how shocks on explanatory variables, such as income, will reverberate on the consumption. These results will be used to formulate various scenarios, inputs necessary for strategic planning of the DSO.

INTRODUCTION

There is an urgent need for precision in the energy demand and consumption forecasts. Both underestimation and overestimation lead to mistaken management of energy contracts, which can unduly burden the DSO (Distribution System Operator). In the Brazilian electricity sector there are strong uncertainties associated with variables such as behaviors of relevant economic indicators or regulation guidelines of governmental agencies which can lead to inaccurate forecasts.
This paper is related to a Research and Development project conducted with a Brazilian DSO named CELESC (Centrais Elétricas de Santa Catarina) which serves approximately 2.4 million customers over an area of 95.346 km2, making it the 7th largest DSO of Brazil.
Decree No. 5163, July 2004 and law 11.943/09, can be considered as the system milestones of the commercialization, generation and distribution of electricity in Brazil. According to these, the marketing is divided into Regulated Contracting Environment (ACR) and the Free Contracting Environment (ACL). The Brazilian DSOs act only in ACR, buying energy by the mean of auction where power plants with the lower prices of electricity are selected. The contracts resulting from these auctions can be as long as 5 year. According to the Brazilian regulation guidelines, the contracted energy to be delivered by the distribution companies must be between 100% and 103% of the energy actually provided to consumers, in order to have full coverage tariff. As many changes and unexpected situations can occur in a five-year horizon, the margin of error in acquiring energy in these auctions is relevant.
Thus, the decision making process concerning energy acquisition needs accurate forecasts of energy demand. It is known that this demand is very influenced by the total number of contracts and deadline, with customers migrating to Free Contracting Environment (ACL), GNP (gross national product) variations, the price of electricity and even the occurrence of large-scale weather phenomena such as El Niño and La Niña. In order to make accurate long-term forecasts, we have to understand the relationships between these variables, or, numerically speaking their elasticity. Besides, all these variables may be subject to shocks that can change the whole scenario. For instance, the Brazilian economic crisis of 2008 negatively impacted the domestic industry and consequently the energy consumption. This paper aims at forecasting energy consumption and demand.

The VAR/VEC Model

As said during the introduction we seek to depict long-term relationships between the electricity consumption and the considered explanatory variables. As presented by Smith (1980, [6]) the VAR (Vector Auto Regressive) model has the form as shown in (1):

$$Y_t = k + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + u_t \qquad (1)$$

where Y_t is the $(n*1)$ vector of variables, k is the $(n*1)$ vector of intercepts, A_i is the $(n*n)$ matrix of variables and u_t is white noise. In this model all variables are considered as endogenous. However the VAR formulation is well suited for stationary variables. Since most economic variables are not stationary we are going to use the VEC formulation (Vector Error Correction) which can be written as presented in (2):

$$\nabla Y_t = \Pi \cdot Y_{t-1} - \sum_{i=1}^{k-1} \Gamma_i \cdot \nabla Y_{t-1} + u_t \qquad (2)$$

where Π and Γ_i are $(n*n)$ matrices which can be deduced from the A_i matrices. The first term corresponds to what is called the cointegration relation which represents the long-term equilibrium. The second term is the error correction term which justifies the name of the model. Thus, the methodology establishes the adjustment, on each period, the long term imbalance regarding short term trajectory. Furthermore, it is important to note that through VEC modeling it is possible to evaluate the

impact of shocks in one variable against another.
As we said many economic series are non-stationary. This property can lead to problems with ordinary least squares estimation. That is why we are going to perform unit root tests before following the methodology to be sure that all the variables have the same order of integration.
From this type of modeling it is possible to estimate price- elasticity of demand for electric energy considering the balance of long-term and short-term adjustments. Anyway, it is worth noting that in the short term an increase in price of electricity causes small reactions in consumers, and in the long term, consumers will adapt to the new values of energy prices, for example, buying more efficient electronics (resulting in less consumption) and even adjusting their routine and the way of electricity consumption. With this, it is possible to infer that the long term consumers tend to be more elastic, i.e., react more significantly to the changes in energy's price.

SHORT AND LONG TERM CONSUMPTION AND DEMAND FORECASTS

Consumption Prediction:

For this analysis, as well as in the study of demand forecasting, forecasting software was developed, whose results will be presented in the next section. It aims at forecasting consumption for each class of consumer (industrial, residential and commercial). For each one of this class influential variables (such as GDP for industrial consumption) were determined.
Unlike the linear regression models found in the literature, or even the autoregressive integrated moving average models (ARIMA), the model considers all the variables as endogenous. This allows depicting long and short term relationships between the variables, and consequently, elasticities. The analysis of the combing's autocorrelation and partial autocorrelation diagrams were done in order to check the occurrence of white noise. Also, items such as identification of lags series, unit root statistical tests, and statistical tests like the *t-statistic*, R2, R2-adjusted, statistic F, etc, are taken into consideration.
Therefore, the method consists in performing a multivariate prediction of demand and consumption, since the pasts instants of all explanatory series are taken into consideration. Still, and once defined the modeling, prediction studies of the explanatory series are carried out, in such a way that makes it possible to quantify the impact of the exogenous series prediction on the energy consumption.

Demand Prediction:

Once made, the consumption forecasts, we ought to do demand forecasts, since demand is a key measure in order to have the electricity network safe. In order to do so we will use consumer's typical curves of CELESC with statistical validation.

To get these curves, it was performed a measurement campaign over 3 to 4 months where thousands of load curves were collected to define the load profile of the typical consumers of the DSO. Figure 1 shows aggregated typical curves, in average demand p.u. (per unit), for residential, commercial and industrial low voltage consumers.

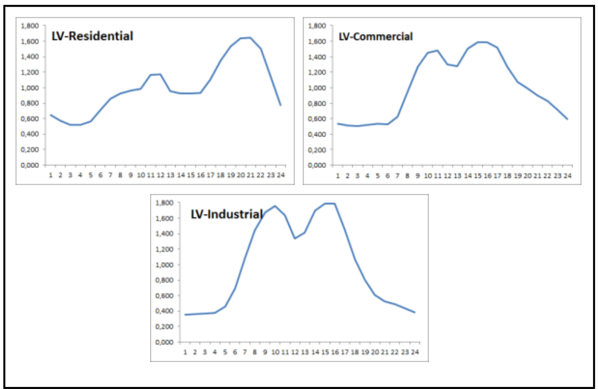

Figure 1 – Consumers Typical Curves for residential, industrial and commercial demand.

From the estimated energy consumption for each month, it is performed the adjustment of the typical curve to the desired energy amount, as shown in (3).

$$D_{A_i} = \left(\frac{E}{\Delta t}\right) * D_{M\,i} \tag{3}$$

Where,

D_{Ai} = adjusted demand in point "*i*".
E = energy estimated by the forecasting model.
Δt = study period.
i = typical curve point

It is noteworthy that the profile of the adjusted demand curve remains unchanged, and that the area below it refers to energy which the typical curve was fitted. Thus, it is possible to determine, from the maximum value among the various points of the load curve, the maximum demand forecast for the month in study.

ANALYSIS OF RESULTS

The objective of this section is to present the results of the studies performed to forecast the energy demand and consumption for residential, commercial and industrial classes of consumers. In order to optimize the results presentation it will be presented in detail the statistical tests obtained in the simulation for the residential class and the graphs with the results of energy demand and consumption forecasting for all classes.

Residential Demand and Energy Consumption Forecasts

The time series that revealed relevant for residential energy consumption and demand forecasts are the number of consumer, the credit for individuals and the residential LV tariff (electricity price).

Figure 2 presents the unit root test results:

Série	Diferenciação	Rejeição de Ho	Probabilidade
Serie1 - Consumo Residencial	Em Nível	0,00000	0,17663
Serie1 - Consumo Residencial	Primeira Diferença	1,00000	0,00100
Serie1 - Consumo Residencial	Segunda Diferença	1,00000	0,00100
Serie2 - Número de Consumidores	Em Nível	0,00000	0,92178
Serie2 - Número de Consumidores	Primeira Diferença	1,00000	0,00100
Serie2 - Número de Consumidores	Segunda Diferença	1,00000	0,00100
Serie3 - Créditos Pessoas Físicas (SC)	Em Nível	0,00000	0,95729
Serie3 - Créditos Pessoas Físicas (SC)	Primeira Diferença	1,00000	0,00198
Serie3 - Créditos Pessoas Físicas (SC)	Segunda Diferença	1,00000	0,00100
Serie6 - Tarifa Conv. B1 Residencial	Em Nível	0,00000	0,83261
Serie6 - Tarifa Conv. B1 Residencial	Primeira Diferença	1,00000	0,00100
Serie6 - Tarifa Conv. B1 Residencial	Segunda Diferença	1,00000	0,00100

Figure 2 – Unit Root Test

By performing unit root test, we find out that all variables are stationary in their first differences. That means that they are integrated of order 1. This means that we shall have a relation of cointegration between these variables and so, perform a VEC model over the dataset.

In sequence, Figure 3 presents the defined coefficients from the long-term relationship between the four interesting variables. This cointegration relation being found, we can compute the model to obtain the predictions. The statistical tests results are also presented. We can notice that the hypothesis H0 of the Durbin-Watson test can be rejected, which means that we have no autocorrelation within the residuals or that we have a high probability of having heteroscedasticity.

Serie2 - Número de Consumidores - Em Nível	0,39610
Serie3 - Créditos Pessoas Físicas (SC) - Em Nível	0,10717
Serie6 - Tarifa Conv. B1 Residencial - Em Nível	-489,73436
Constante	-936653,45062

Estatísticas do modelo

Índice	Valor
EQM	816393850,41645
R2	0,48028
R2 Ajustado	0,47344
Soma dos resíduos a...	17760530732,57843
Estatística f	35,11647
Probabilidade f	0,00000
DW	0,67852
Probabilidade DW	0,00000
Teste de heteroceda...	0,87632

Figure 3– Statistical Tests Results

At last, Figures 5 and 6 illustrate the energy demand and consumption for residential consumers of CELESC. In Figure 5 the blue line represents values that actually occurred (time series), the green line represents how the model is fitted, and the red line represents the forecast for the next 5 years.

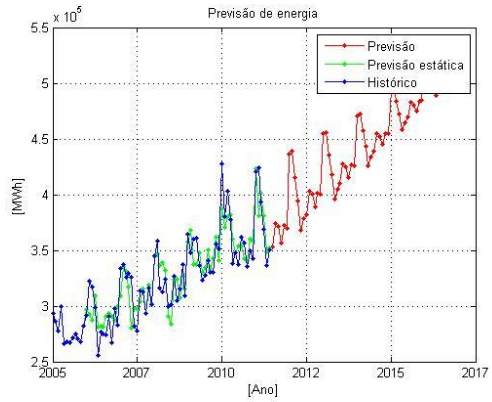

Figure 4 – Residential Energy Consumption Forecast

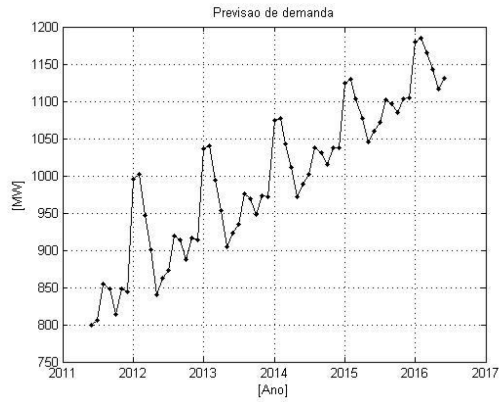

Figure 5 – Residential Demand Forecast

Analogously, Figures 6 to 9 present demand and energy consumption for commercial and industrial consumers of CELESC.

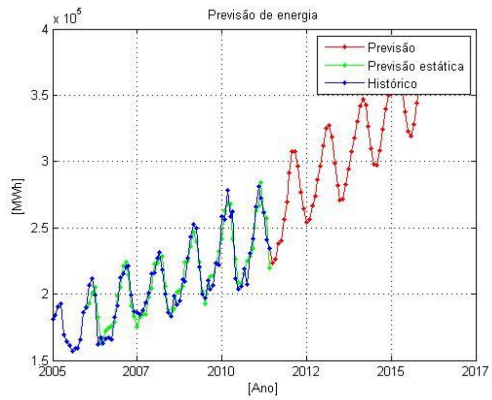

Figure 6 – Commercial Energy Consumption Forecast

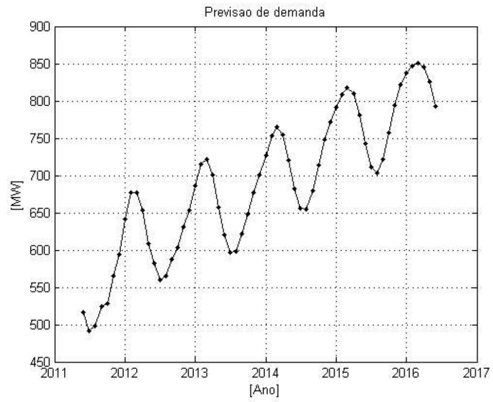

Figure 7 – Commercial Demand Forecast

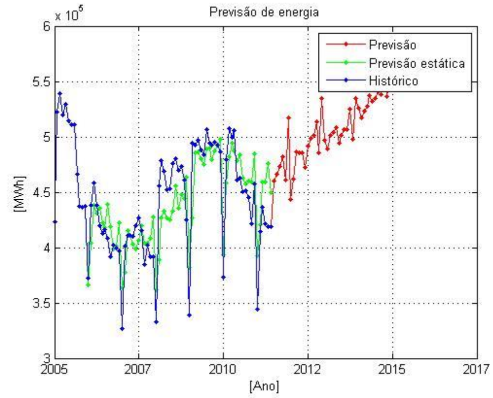

Figure 8 – Industrial Energy Consumption Forecast

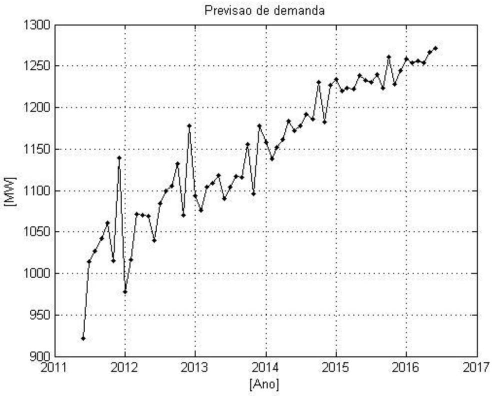

Figure 9 – Industrial Demand Forecast

CONCLUSION

This paper presents different approaches from those commonly used for energy consumption and demand forecasts for the various classes of consumers, as well as the determination of estimated price-elasticity of demand for electric energy through VEC modeling.

For the forecast itself, it is performed a multivariate prediction where external shocks impacting the explanatory variables, have significant impact on the variable to be explained, i.e., the consumption of electricity. In order to compute demand forecast, it is used the data provided by the energy consumption forecasts, and CELESC's consumers typical curves. Finally, it should be noted that the figures presented in this paper are the results of new software developed in the referenced R&D project environment.

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