ENERGY CONTRACTING FOR LARGE CONSUMERS IN BRAZIL: A REAL CASE STUDY

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ABSTRACT

In Brazil, large consumers have different alternatives to contract energy. The type of contract and its parameters are important decision variables for consumers who aim to reduce their electricity bill. Here, it is proposed a model to assist large consumers to take these decisions. This model is based on a statistic auto regressive (AR) model to forecast monthly energy consumption and maximum demand in order to establish the best contract for the consumer. The performance of the forecast-based model is evaluated through statistical analysis and by comparison with a simpler method that considers the average values. Different contracting environments are investigated. Results show the importance of adequate forecasting in determining the most cost-effective contract strategy.

I. NOMENCLATURE

D	Contracted demand (kW).
T_D	Tariff of contracted demand ($/kW).
E^p	Peak energy consumption (MWh).
T_E^p	Tariff of peak energy consumption ($/MWh).
E^{op}	Off-peak energy consumption (MWh).
T_E^{op}	Tariff of off-peak energy consumption ($/MWh).
Pen_D	Penalty for exceeding contracted demand.
D_{verif}	Verified maximum monthly demand (kW).
T_D^{exc}	Tariff of demand exceeded ($/kW).
E_{gen}^p	Energy consumption supplied by local generators (MWh).
c_{gen}	Local generation cost ($/MWh).
p	Energy price established in contract ($/MWh).
Q	Energy contracted for the month (MWh).
C_{spot}	Cost of energy in the short-term market ($).
$TUSD_E$	TUSD for energy consumption ($/MWh).
E	Energy consumption of the month (MWh).
$TUSD_D^p$	TUSD for demand on peak hours ($/kW)
D^p	Demand contracted for the use of distribution network on peak hours (kW).
$TUSD_D^{op}$	TUSD for demand on off-peak hours ($/kW).
D^{op}	Demand contracted for the use of distribution network on off-peak hours (kW).
π	Average spot price of the month ($/MWh).
B	Backshift operator.
$\varphi(B)$	Autoregressive polynomial of degree p ($\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$).
y_t	Dependent variable at instant t.
α	Constant of dynamic regression model.
$\boldsymbol{x}_t$	Vector of explanatory variables at instant t.
$\boldsymbol{\beta}$	Vector of coefficients of explanatory variables.
ε_t	Residue at instant t.
D_t	Maximum demand in month t.
UD_t	Number of 'normal university' days in month t.
$Tmin_t$	Average minimum temperature in month t.
E_t	Energy consumption in month t.
$Tmax_t$	Average maximum temperature in month t.

II. INTRODUCTION

In Brazil, large consumers (characterised by installed load equal or greater than 3MW) have different options for contracting energy [1]. Depending on the choice, large consumers can be in a Regulated Contract Environment (RCE) or in a Free Contract Environment (FCE).

In RCE, large consumers, called captive consumers, buy energy from a utility company (that integrates the roles of distribution network operator and energy supplier). The billing is done monthly based on tariffs that essentially provide the revenue required by the utility company to cover its costs plus a pre-defined profit [2]. A contract in RCE includes monthly payments by energy consumption (in MWh) and demand (in kW).

In FCE, large consumers, called free consumers, buy energy from a generation company, through a commercialisation company. Energy price is determined between the participants. A contract in FCE includes payments for the amount of energy bought and for network usage. The consumer must establish a contract with the utility and the payment is made through a tariff, which can be in distribution or transmission levels, depending on the consumer connection.

Both contract environments have a risk associated to their parameters. In RCE, demand should be defined (ex-ante) in the contract for all the months of the current year. Utilities use the declared demand for planning purposes. For this reason, there is a heavy financial penalty for consumers that exceed their contracted demand. Thus, the corresponding demand forecasts are valuable information to captive consumers.

In FCE, the risk is present in the quantity of energy bought in the contract. Free consumers generally distribute the total amount of energy contracted in a monthly basis. The consumer must define the energy quantity for each month. In case the energy consumed for one month is greater than the contracted energy, the difference should be paid using the spot price. In Brazil, the spot price is a systemic variable [3] and used for the short-term energy market. The main characteristic of the spot price is its unpredictability and, for the consumers view point, it should be avoided. This framework makes forecasts of energy consumption essential information for free consumers.

In this paper, historic data from a university in Rio de Janeiro (as a large consumer) is used to develop two forecast models: one for maximum demand and one for energy consumption. The forecasts will be used as parameters for the RCE and FCE contracts. The objective is to provide this particular large consumer with the most cost-effective contract. The forecast models are made by dynamic regression using explanatory variables that are closely related to the energy consumption and maximum demand of the large consumer.

The paper is organised as follows: section II presents the formulation of monthly costs for each one of the energy contracts analysed. Section III explains the developed autoregressive models. Results are presented and discussed in section IV. Finally, in section V conclusions are drawn.

III. ENERGY CONTRACTS

This section presents in more detail the formulation of costs associated to contracts for captive and free consumers. In addition, the use of generation owned by the captive consumers (an approach commonly used to reduce energy costs) is presented.

Captive Consumers

Captive consumers are usually billed by demand and energy, both peak (17:30 to 20:30) and off-peak hours. In this work the study is limited to the so-called 'green tariff' group, where demand tariff is unique and energy consumption tariff is different in peak and off-peak hours.

The formulation of total monthly cost ($C_{captive}$) of a captive consumer contract is given in (1).

$$C_{captive} = D \cdot T_D + E^p \cdot T_E^p + E^{op} \cdot T_E^{op} + Pen_D \qquad (1)$$

The term Pen_D corresponds to the charge on the amount of demand that exceeds the contract demand (D), and can be formulated as in (2).

$$Pen_D = \begin{cases} \left(D_{verif} - D\right) \cdot T_D^{exc}, if\ D_{verif} > 1.05 \cdot D \\ 0,\ if\ \ D_{verif} \le 0.95 \cdot D \end{cases} \qquad (2)$$

The consumer is given a tolerance of 5% above the verified exceeded demand. The value of T_D^{exc} is typically around three times the regular tariff T_D.

Captive Consumers with Generators

Because the tariff for the peak hours is expensive, it is common to find captive consumers using local fossil fuel-based generation (owned by them) to supply partially or totally the energy consumption during this period as the corresponding cost is much lower. The formulation of monthly costs of the contract of captive consumers with generators is presented in (3).

$$\begin{aligned} C_{captive}^{gen} = D \cdot T_D + E^p \cdot T_E^p + E^{op} \cdot T_E^{op} + Pen_D + \\ + E_{gen}^p \cdot c_{gen} \end{aligned} \qquad (3)$$

The expression is similar to (1), with the difference of an addition term representing generator costs.

Free Consumers Contract

The large consumer in study is connected to the distribution level, so the payment for the network usage should be done to the corresponding utility according to the Distribution Use of System Tariffs (TUSD in Portuguese). In Brazil, the TUSD are applied to energy consumption, as well as demand during peak and off-peak hours.

In order to promote the development of low carbon energy sources (small hydro, solar, wind, biomass), Brazilian legislation established discounts for consumers who buy energy from these generators [4]. The discount is in a part of the TUSD for demand. These discounts can be 50% or 100% depending on the low carbon energy contracted by the free consumer.

Considering the monthly distribution of the total amount of contracted energy, the formulation of the total monthly cost for a free consumer contract is given in (4).

$$\begin{aligned} C_{free} = p \cdot Q + C_{spot} + TUSD_E \cdot E + \\ + TUSD_D^p \cdot D^p + TUSD_D^{op} \cdot D^{op} \end{aligned} \qquad (4)$$

The term C_{spot} is nonzero if the final consumption is greater than the contracted one, as shown in (5).

$$C_{spot} = \begin{cases} \pi \cdot (E - Q), & if\ \ E > Q \\ 0, & if\ \ E \le Q \end{cases} \qquad (5)$$

Although, in practice, the spot prices are weekly, for simplicity the monthly average is used.

IV. DYNAMIC REGRESSION MODELS

The forecast models were applied using the historical data from the university in Rio de Janeiro (as a large consumer). To obtain an adequate model, the main characteristics of the energy profile of the university were analysed through a dynamic regression model This model combines the behaviour of a dependent variable (energy consumption and maximum demand, in this work) with the effect of explanatory variables, neglecting the hypothesis of independency of errors [5]. In general, a dynamic regression model can be defined as in (6).

$$\varphi(B) \cdot y_t = \alpha + \boldsymbol{\beta} \cdot \boldsymbol{x}_t + \varepsilon_t \qquad (6)$$

Explanatory Variables

The characteristics of the energy profile of the studied consumer revels two main aspects used to define the explanatory variables. First of all, being a university, the monthly energy consumption and maximum demand are closely related to the number of lectures. Months outside the academic year, for example, tend to have less energy consumption. Thus, a variable containing the number of 'normal university' days in each month has an important relation with, and can 'explain', the corresponding consumption profile, so is selected as an explanatory variable.

The second characteristic observed was the large use of air conditioners, which in turn is closely related to the temperature. Thus, the monthly averages of the maximum, minimum and mean temperature were also defined as explanatory variables.

Forecast Models

For the forecast models, historical data of the dependent variables (energy consumption and maximum demand) and explanatory variables were used. The period considered (with historic data) is from January 2004 to April 2012 (100 months). The period of analysis was divided in an in-sample (from January 2004 to April 2011) and an out-of-sample (from May 2011 to April 2012) data sets.

The forecast models and their coefficients were estimated using the software Forecast Pro for Windows (FPW) [6] through a bottom-up strategy [5]. The variables were considered in logarithmic scale in order for the coefficients in $\boldsymbol{\beta}$ to reflect the relative variation of the dependent variables as a function of the relative variation of the explanatory variables. This relation is known as coefficient of elasticity [5]. To assess the performance of the models, the coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE) statistics [5] are used.

Maximum Demand Forecast Model

The dynamic regression model obtained for forecasts of maximum demand is presented in (7).

$$\begin{aligned}\ln(D_t) = 0.02 \cdot \ln(UD_t) + 1.01 \cdot \ln(Tmin_t) + \\ +0.21 \cdot \ln(D_{t-6}) + 0.23 \cdot \ln(D_{t-24}) - 2.50\end{aligned} \quad (7)$$

The signal of the coefficient of UD_t shows that the greater the number of 'normal university' days, the greater the maximum demand. This is the expected relation between D_t and UD_t. The same behavior is observed in $Tmin_t$. The model also contains lags of the dependent variable ($t-6$ and $t-24$) showing the existence of seasonality. The variables of maximum and mean temperature were discarded due to the lack of relevance to the model.

The model leads to an R^2 equal to 79% and an MAPE of 5.2% for in-sample forecasts. Out-of-sample MAPE was between 1.3% and 5.3%. These metrics are appropriate, and the MAPE of forecasts out-of-sample are in an acceptable interval.

Energy Consumption Forecast Model

The dynamic regression model for forecasts of energy consumption is presented in (8).

$$\begin{aligned}\ln(E_t) = 0.01 \cdot \ln(UD_t) + 0.74 \cdot \ln(Tmax_t) \\ +0.30 \cdot \ln(E_{t-12}) + 0.33 \cdot \ln(E_{t-24})\end{aligned} \quad (8)$$

Analogously to the maximum demand forecast model, the signals of the coefficient of UD_t and $Tmax_t$ show that the greater the number of 'normal university' days and minimum temperature, the greater the energy consumption. Again, the model contains lags of the dependent variable ($t-12$ and $t-24$) showing the existence of seasonality. The variables of minimum and mean temperature were discarded due to the lack of relevance to the model.

The model gives an R^2 of 79% and a MAPE of 4.8% for in-sample forecasts. Out-of-sample forecasts obtained a MAPE between 1.4% and 9.2%. The performance metrics are similar to the previous model. The interval of MAPE out-of-sample is greater than the one observed before but is still an acceptable value.

V. RESULTS

To evaluate the performance of the proposed models and most cost-effective contract, a cost analysis is first presented for only one month (September) and then for the whole year. All costs simulations are made in a contract simulator that includes all aspects and formulations presented in Sections I and II.

Initiating with the monthly analysis, for comparison, contract parameters will be produced by the proposed forecast models and by a simpler approach based on the historical monthly average (for the previous two years). The latter will be called the 'simple average method'.

In Fig. 1, for the out-of-sample data set period, the forecasts for energy consumption and maximum demand given by the proposed model and the simple average method are shown.

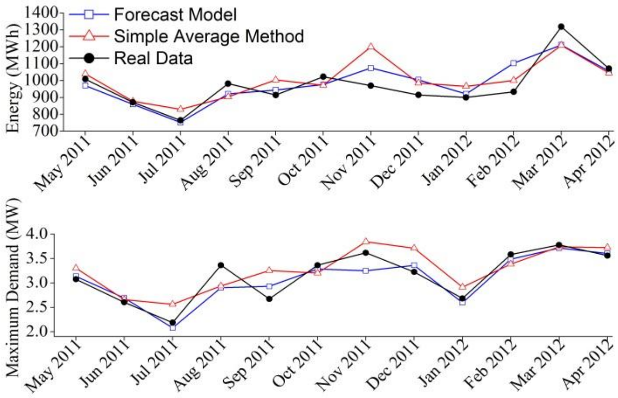
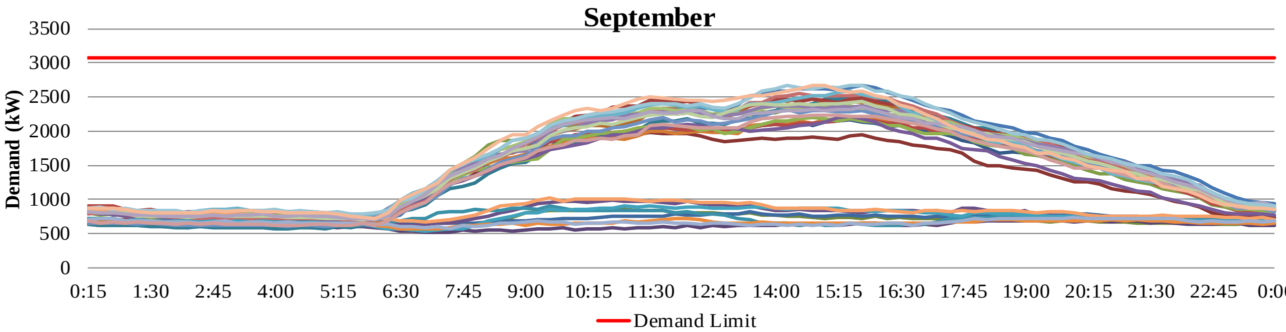


Fig. 1. Estimated energy consumption and maximum demand.

The month of September 2011 was chosen given the highest MAPE values for the out-of-sample forecasts in both models. Thus, this is one of the worst case results, and other months present a best performance. All tariffs used were the ones valid from May 2011 to April 2012. The local generation data (production and cost) was obtained from the university. The energy price for a free consumer contracts is the value typically defined in FCE contracts.

In Fig.2 is presented the result screen of the contract simulator. The partial and total costs for a captive consumer contract by using the maximum demand forecast model are presented. The consumption profile (demand curves) is also shown. The flat curves correspond to weekends, which have less energy consumption. The other curves correspond to week days, when generally the monthly maximum demand occurs.

The results for all the contracts types and the corresponding comparison with those given by the simple average method are shown in Table I. As expected for all contracts, the forecast models provide contract parameters that result in lower costs. The cost difference reaches the value of $17k for a free consumer contract with low carbon energy (100% discount).



Simulation Results - Captive Consumer Contract				
Contracted Demand (kW)	2,931.00	Off-peak Consumption (MWh)	804.43	
Contracted Demand Cost	$52,299.65	Off-peak Consumption Cost	$211,866.29	
Demand over Limit (kW)	0.00	Peak Consumption (MWh)	110.11	**TOTAL COST**
Demand over Limit Cost	$0.00	Peak Consumption Cost	$233,816.59	
Total Demand Cost	**$52,299.65**	Total Consumption (MWh)	914.54	
		Total Consumption Cost	**$445,682.88**	**$497,982.53**

Fig. 2. Result screen of contract simulator for a captive consumer contract (one month).

Table I. Total energy contract costs (one month)

Consumer Contract	**Contract Cost ($\$ \cdot 10^3$)**	
	Forecast Model	**Simple Average**
Captive	497.89	503.75
Captive with Generators	393.44	399.22
Free	527.90	538.97
Free (low carbon, 50% discount)	440.05	453.67
Free (low carbon,100% discount)	368.26	385.28

It is important to highlight that avoiding the exposure to penalties is not enough to establish an adequate energy contract for a large consumer. As it can be seen in Fig. 2, the parameters provided by the simple average method do not result in penalties either. However, over-contracting can occur, leading to a significant increase in costs. Thus, contract parameters more adjusted to the profile of the consumer, such as the ones provided by the developed forecast models, are valuable for the planning of energy contracts.

Finally, in Table II, the annual costs of the different contract types are presented (considering out-of-sample period). As the results in Table I confirmed the better performance of the forecast models over the simple average, forecast results are used as contract parameters.

Table II. Annual costs of energy contracts

Consumer Contract	**Annual Cost ($\$ \cdot 10^6$)**
Captive	6.17
Captive with Generators	4.95
Free	6.64
Free (low carbon, 50% of discount)	5.54
Free (low carbon, 100% of discount)	**4.64**

The contract as a free consumer with 100% discount (in the corresponding part of the TUSD) indicates a much lower annual cost. The discount makes a significant difference in comparison with the other contracts within the FCE. On the other hand, the use of local (own) generation provides also significant savings for a contract in RCE, being as well an attractive option for this consumer.

VI. CONCLUSIONS

This work presented forecast models (that estimate monthly maximum demand and energy consumption) to assist determining the most cost-effective energy contracts for large consumers in Brazil.

For the studied case, a university, it was found that the free consumer contract with a low carbon energy generation company is the best choice to reduce energy contract costs. Results indicate that a contract as captive consumer with own local generation is also an attractive choice.

VII. ACKNOWLEDGMENTS

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