A HYBRID MODEL APPROACH FOR FORECASTING ELECTRICITY DEMAND

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ABSTRACT

This paper presents the forecast of electricity consumption based on mathematical models by using the available historical consumption, with daily resolution, including upscaling, applying a hybrid model that incorporates multiple linear regression with artificial neural networks. Therefore, the hybrid model exploits both the unique features of the regression model and of the artificial neural network to determine different patterns. Thus, it is advantageous to model linear and nonlinear patterns separately using different models and then combine the forecasts to improve overall performance modelling and forecasting.

The applied methodology is very reliable given that the forecast errors are close to zero, and the observed differences are justified essentially by temperature effect.

INTRODUCTION

The electricity consumption analysis and its forecast is an essential tool for energy management and planning.

Given the importance of energy demand evolution, various models have been proposed overtime. Recently, hybrid models applications incorporating intelligent models such as artificial neural networks along with other statistical approaches have been the subject of study in forward analysis.

To develop this study, there was an extensive research of the different methodologies recently approached and was carried out a series of tests to assess the accuracy and reliability of the different methods. In an exploratory analysis, using time series models to decompose the data into its main components (trend, cycle and seasonality) is visible that the behaviour of different voltage levels is quite distinct from each other. For that reason, a model for each voltage level was developed.

All research and respective statistical analysis was performed using the statistical software R.

FORECASTING ELECTRICITY DEMAND

The analysis of electric consumption and its forecast comprises the following steps:

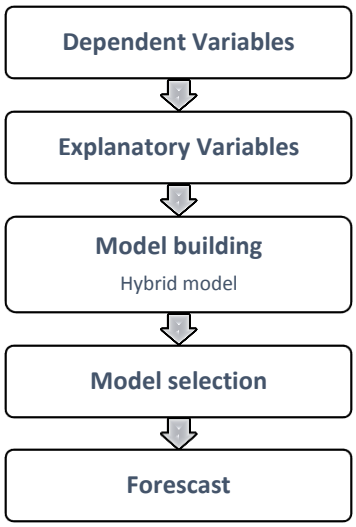

Figure 1. Flowchart of forecasting electricity demand

Dependent variables

A daily resolution was used for dependent variables to have a greater number of data and to have more accuracy, thus reducing the forecast error, namely temperature effect errors.

A model for each dependent variable was created, that is, for Very High Voltage (VHV), High Voltage (HV), Medium Voltage (MV), Special Low Voltage (SLV), Standard Low Voltage (LV) and Public Lighting Low Voltage (PL).

The clients connected to the higher voltage levels network are remotely metered, therefore the exact daily energy consumption can be known. It should be noted that telemetered clients account for 65% of total consumption, and the readings are made with 15 mins intervals. On the other hand, the majority of clients, specially those connected to the LV grid, are manually read every 3 months. This makes it impossible to know exactly the amount of energy consumed each day. So, with regard to SLV, an extrapolation of the daily consumptions using load diagrams of a representative sample of this voltage level was performed.

For public lighting, it was created a mathematical model in

which it is establishes a relationship with the number of nocturnal hours.
Concerning the Standard LV, the consumption of this voltage level is obtained by subtracting from the total consumption of low voltage, the consumption of PL and of SLV.

Explanatory Variables

	VHV	HV	MV	SLV	LV	PL	Font
Historical Consumption	x	x	x	x	x	x	EDP Distribuição
GDP		x	x	x			IMF
Private consumption					x		IMF
Temperature			x	x	x		NOAA
Inertia	x	x	x	x	x	x	
Calendar	x	x	x	x	x	x	
Number of nocturnal hours						x	IPMA
Energy efficiency		x	x	x	x	x	ERSE Ministry of Economy
Electric vehicles					x		EDP MOP
Self-consumption					x		DGEG/ EDPD Estimate

Table 1. Explanatory variables

Trends resulting from macroeconomic effects

For the analysis of development trends, econometric models were prepared in order to create trend variables by voltage level which, in turn, were incorporated in consumption prediction models. Hence, it could be verified that the behaviour of the consumption of the electricity for the voltage levels High Voltage (HV), Medium Voltage (MV) and Special Low Voltage (SLV) was sensitive to economic activity measured by Gross Domestic Product (GDP). On the other hand, the Standard Low Voltage (LV) presented statistical significance when related to private consumption.

Temperature effects

In order to establish the relationship between temperature and consumption of different voltage levels, the consumption of external factors (GDP, Private Consumption) and normalisation of consumption data were chosen to be comparable.
The voltage levels VHV and HV were not sensitive to temperature, and the scatter plots of these voltage levels indicated no connection with the variable under study.
It can be seen that the voltage levels that were sensitive to temperature (MV, SLV and LV) behave differently when crossed with this variable. The consumption of MV is more scattered and with greater variability. On the other hand, the LV intakes present values with lower variability and are more sensitive to lower temperatures. The exact opposite occurs with SLV, which proves to be more sensitive to higher temperatures. For the purpose of forecasting, daily values of normal temperature (the temperature that would be expected for a given day) were calculated assuming the mean of the average temperatures of a historic of 40 years of daily data of six geographically distributed Portuguese cities: Beja, Bragança, Castelo Branco, Faro, Lisbon, Oporto.

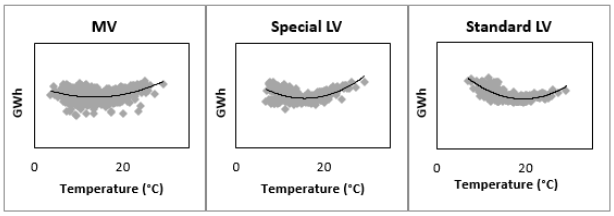

Figure 2. Relationship between temperature and electricity consumption

Inertia of consumption

One of the variables taken into account in the models was the electricity consumption in the previous day. Indeed, it was found that the previous working day of consumption shows statistical significance in forecasting models at all voltage levels. In theory, the impact of this variable is due to the inertia of consumption, mostly resulting from temperature sensitivity. For this reason, in this work, separate inertia is taken into account.

Calendar effects

As depicted in the following graphs, calendar has a strong effect on electricity consumption.

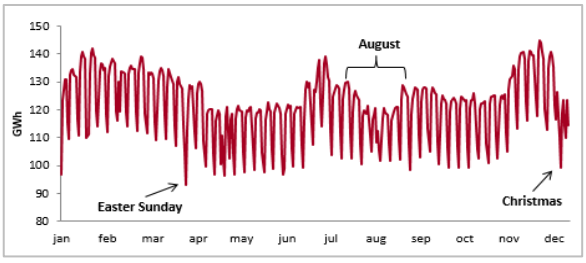

Figure 3. Daily electricity consumption diagram for one year

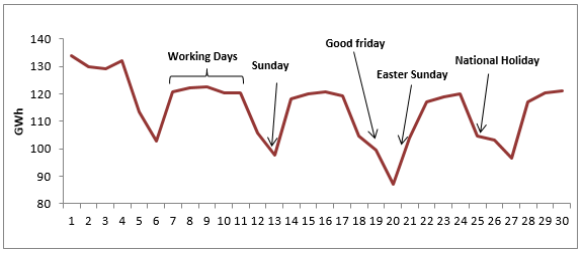

Figure 4. Daily electricity consumption diagram for one month

In order to evaluate these same effects binary variables (dummy variables) were integrated into the model. They represent:
- Holidays
- Days after holidays
- Bridge Holidays (may occur on a Monday or Friday)
- Special days such as Christmas, Easter Sunday or New Year's Day.

Regarding the weekly cycle, binary variables representing the weekdays were included in the model:
- Working days
- Saturdays
- Sundays

In relation to the annual cycle, binary variables that portray the months of the year that affected the consumption of electric energy were also included in the model.

Energy efficiency measures

The electricity consumption forecast for the residential, service and industrial sectors took into account the projected savings from the implementation of measures to promote efficiency in the scope of the various Plans for the Promotion of Efficiency in Electric Energy Consumption (PPEC), as well as the National Action Plan for Energy Efficiency (PNAEE). In addition to this, the campaign to distribute efficient lamps by the Ministry of Economy (ME) has also been taken into account.
Given that the forecasting models are already affected by the impact of the energy efficiency measures, the difference in incremental impact value over the reference year was assumed for the following years. Moreover, it was considered that the energy efficiency measures adopted in years prior to the forecast would be maintained in the future, due to the adoption of efficient practices that underpinned the measures implemented.

Electric Vehicles

In the calculation of consumption forecasts, the resulting consumption of electric vehicles (EV) was included. Obtaining the first effective data on energy consumption directly related to the gradual integration of the electric vehicle in the car fleet allowed us to conclude that the adoption of the electric vehicle did not occur with the expected intensity.
The values now presented derive from the necessary revision to the initial forecasts and were obtained by proportional adjustment based on the actual consumption of the years 2013-2014.

Year		Consumption EV (GWh)
2013	Verified	0,12
2014		0,17
2015	Forecast	0,32
2016		0,54
2017		0,89
2018		1,46
2019		2,29
2020		3,44
2021		3,90

Table 2. Electric vehicle consumption and forecast

Self-consumption

The following figure shows the evolution of self-consumption between 1994 and 2014, allowing for a significant change in the evolution of this energy since 2002. In 2014 a legal regime was established for the appearance of small production units, with or without connection to the public power grid, destined to the self-consumption in the facility (UPAC - units of production for self-consumption). To the extent that the forecast models are already affected by the implicit consumption of final consumption, it was assumed that this impact, for the forecast period, would exhibit the same behaviour. For this reason, no incremental value of this same effect was incorporated into the resulting values of the models.

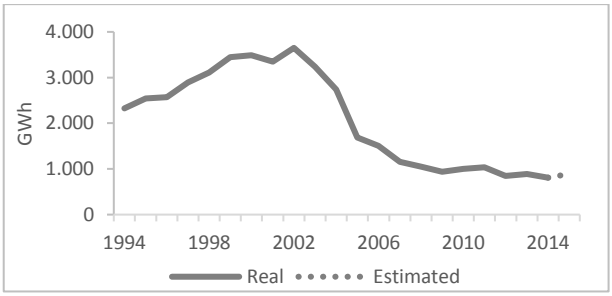

Figure 5. Evolution of self-consumption

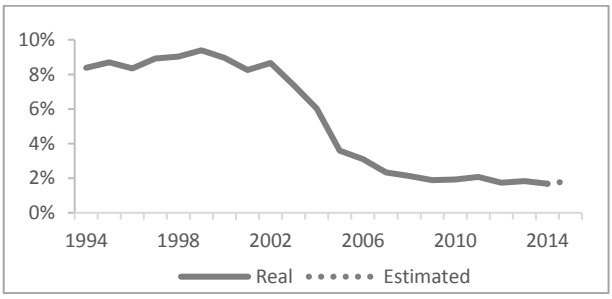

Figure 6. Weight of self-consumption in the total consumption of the Continental Portugal

Model building - Hybrid model

The proposed methodology of the hybrid model consists of two steps. In the first step, the multiple linear regression model (MLR) is used to analyse the linear part of the problem. In the second step, the neural network model is developed to model the residues resulting from the MLR model.
It is known that the MRL model can not capture the nonlinear structure of the data, so the residuals of the linear model will contain information about nonlinearity. The results of the neural network model are then used as predictions of the error terms for the MLR model.
A training of known values that allow us to estimate, depending on certain variables, what will be the error associated with the forecast obtained through the regression model was performed.
The hybrid model thus explores the unique feature of the regression model as well as the neural network model in order to determine different patterns. Thus, it is advantageous to model linear and non-linear patterns separately using different models, and then combine predictions to improve overall modelling and prediction performance.

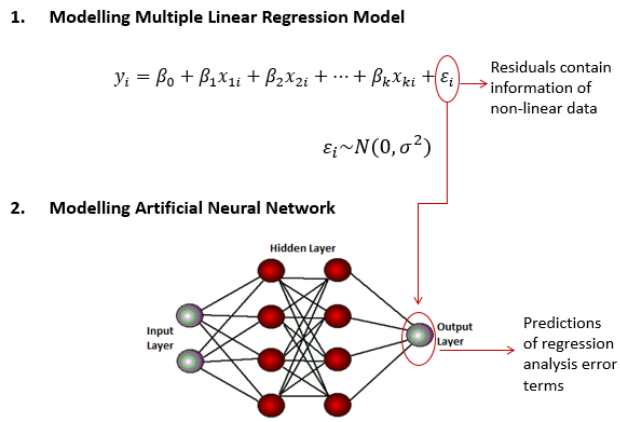

Figure 7. Hybrid model approach for forecasting electricity demand

Model Selection

To measure the accuracy of each model the value of the coefficient of determination (R^2) was calculated. The coefficient of determination, also called R^2, is one way to evaluate the quality of the model in relation to the observed values. The R^2 varies between 0 and 1 (or 0 to 100%), indicating, in percentage, how much the model can explain the observed values.
The higher the R^2, the more explanatory the model is, the more adjusted the forecasts are relative to the actual data.
The graph shows the results of the coefficient of determination in both models, which increases at all voltage levels when hybrid model is applied.

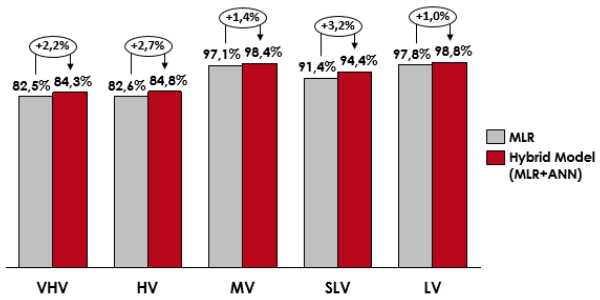

Figure 8. Accuracy comparison of MLR model and Hybrid model

The R^2 value increases at all voltage levels when the hybrid model is applied, as depicted above.
Of all the tested methodologies, the hybrid model (MLR + ANN) was the most accurate and closer to the real values (higher R^2).

Forecast

In order to assess the reliability of the developed models, a comparative analysis of the actual energy input and consumption data, for each voltage levels was performed. The consumption that was estimated using forecasting models made in the beginning of the year 2015. As shown in the graphs below, the applied methodology is very reliable given that the forecast errors are close to zero, and the observed differences are justified essentially by temperature effects.

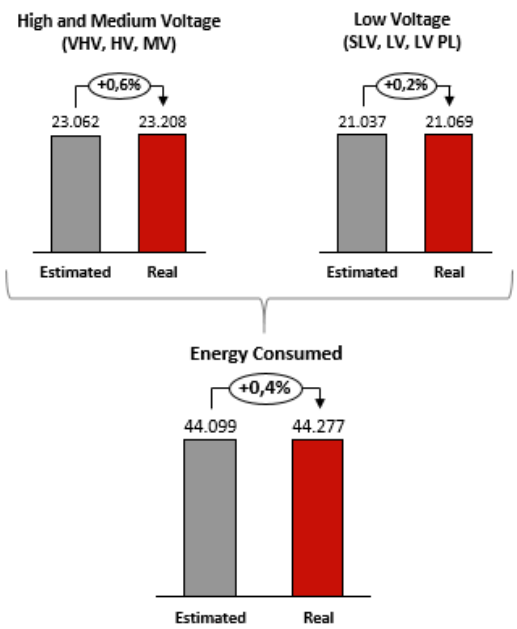

Figure 9. Estimated vs. Real Energy Consumed in Portugal in 2015 (GWh)

CONCLUSION

With this work a correct evaluation of consumption of the different voltage levels for the energy balance could be carried out, detecting possible inconsistencies in the values and allowing their correction in an effective and timely manner.

The factors that determine the consumption of electricity and quantify the respective impact could also be evaluated. Furthermore, the electricity consumption forecasts obtained are currently being used for the preparation of reports such as the Budget Planning, Business Planning, and Development and Investment Planning of the Electricity Distribution Network.

In addition to using voltage levels forecast, EDP Distribuição is studying other segments behaviours, namely, profiles targeting, grouping by geography, economical clusters, among other factors.

This model has great potential since it is possible to detect patterns within each voltage level that can be then exploited and forecasted. By doing so, a better understanding of the future consumer can be acquired.

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