Power Demand Forecasting through Social Network Activity and Artificial Neural Networks

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***Abstract*—Long-term and short-term term national power demand forecasting is a well known and open issue for many countries. In this paper, we focus and study the short-term Peruvian national power demand forecasting. Thus, we tackle this problem using indirect and direct method for prediction. The former method relies on Social Network Activity to estimate national needs using regression models. The latter method is based on Artificial Neural Networks (*ANNs*). The network was used subsequently for predictions of the power for the last day of April, May and June 2016. The result was highly satisfactory with a mean absolute percentage error (MAPE) of 0.36 % for April and 0.34% in May and June. The ANN cumulative model proved to be a fast, reliable and accurate method for predicting power demand in Perú. In the case of the social activity generated by tweets, there is an increase in the MAPE values of an order of magnitude, reaching a maximum value of 7.3% for June. Nevertheless, the power demand forecasting using Twitter posts is a good indicator as a first approximation.**

Keywords—Artificial neural networks, Power demand forecast, social network activity, Power systems.

I. INTRODUCTION

Power demand is crucial for social, economic and environment sustainable development of a country. Knowing the power consumed is vital for agriculture, industry, health, access to water, education, security, etc. Consequently, an accurate estimation of future demand is critical to prevent potential need at a country level. In the current study, we propose two different methods to predict power demand. The first method relies on Social Network Activity (*SNA*). Nowadays, human activity is captured by people's activity in social networks such as Twitter, Facebook or Instagram. For instance, Bollen *et al.* provide a platform to model collective emotive trends linked to social, political, cultural or economic events [4] using tweets. In [5] Borge *et al.* made a quantitative analysis of the structural and dynamical patterns emerging from the activity on Twitter around the anti-austerity (15M) movement in Spain. Unemployment was another studied phenomenon by Llorente *et al.* [14] using Twitter. Authors found that regions that exhibit more different mobility fluxes, and correct grammatical styles have lower unemployment rates.

The second method is based on Artificial Neural Network (*ANN*), which is a computational model inspired in the natural neurons to process information mimicking the physiologic structure and behavior of the brain. There are multiple connections between units within and between layers. These connections have strengths or ”weights” that are ”learned” by the network. ANN can approximate a nonlinear relationship between the input variables and the output of a complicated system. The main advantage of an ANN model is its self-learning capability [20]. Kreider and Wang [13] have applied ANNs to predict power use in commercial buildings. In particular, the authors have implemented the method as part of their work on the application of expert systems to heating ventilating and air conditioning (HVAC) diagnostics in commercial buildings. They have used ANNs to determine with good accuracy the energy use of chillers by using hourly averaged data collected from the system. Curtiss *et al.* [7] demonstrated how ANNs could be used to optimize the energy consumption in a commercial-scale HVAC system. Kalogirou and Bojic [12] have been used ANNs for the prediction of the energy consumption of a passive solar building. The use of ANN in building energy prediction has been investigated by many researchers (*e.g.*, [2] and [8]). Azadeh et al. [3] research work used ANN for forecasting electrical consumption. To train the ANN, preprocessed data have been extracted from the time series techniques for the first time; demonstrated superiority over ANN and conventional regression model. A full review for electrical energy forecasting can be found in [1] where artificial intelligence (AI) methods such as support vector machine (SVM) and ANN are used.

In this paper, we used both methods to predict the power demand in Perú, social network activity, and ANN models.

The remainder of the article is organized as follows: Section II presents the basic concepts, while Section III describes the datasets used in this study. Finally, Sections IV and V describe the methodology, present the results of our study and concludes the paper, respectively.

II. BASIC CONCEPTS

In the present section, we introduce some basic concepts, for our study, like (A) Regression models, (B) Artificial Neural Networks and (C) the Mean Absolute Percentage Error.

A. Regression model

Regression is a method for capturing the relationship between a dependent variable and one or more independent variables [6], [19]. For our study, we use three different regression models:

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*a) First order (*FOLM*):* regression model is used to represent a linear relation between y and x as shown in Equation 1.

$$y = \beta_0 + \beta_1 x \tag{1}$$

Where y is the response variable (*i.e.,* power demand), x is the variable factor (*i.e.,* amount of tweets), β_0 and β_1 are the intercept and the slope, respectively.

*b) Second order (*SOLM*):* or polynomial regression model makes the response surface curvilinear (*c.f.,* Equation 2).

$$y = \beta_0 + \beta_1 x + \beta_1 x^2 \tag{2}$$

c) Local regression: uses a local fitting model. Thus, the fit is performed using the nearest points in the neighborhood of x, weighted by their distance from x.

B. Neural Network based Model

The Rumelhart-Hinton-Williams multilayer network that we consider here is a feed-forward type network with connections between adjoining layers only. Networks have hidden layers between the input and output layers.

The input-output relationship of each unit is represented by inputs x_i, outputs y_i, connection weights w_i, threshold and differentiable function θ as follows:

$$y = \varphi\left(\sum_{i=1}^{k} w_i x_i - \theta\right) \tag{3}$$

Usually, the function φ is called the activation function, which is a bounded and monotone differentiable function such as the sigmoid function represented by Equation 4, where a is the slope parameter of the function. [10]

$$f(x) = \frac{1}{(1 + e^{-ax})} \tag{4}$$

The learning rule of the neural network is known as Back Propagation algorithm [16] and consists in the use of the gradient descent method to find a set of weights so that the error between the desired output and the output signal network is minimized.

Neural network modeling process comprises three primary steps related to experimental data: training, testing and predicting. Network training is the process of adjusting the network connection weight in a way that explanatory and response values match the data as closely as possible. Testing data are used for checking the training. Finally, validating data are used for studying model accuracy. A comprehensive reference on neural networks can be found in [11].

C. Mean Absolute Percentage Error

The Mean Absolute Percentage Error (*MAPE*) is a metric to quantify how accurate a forecasting method is [15]. This metric is considered as a standard for examining the quality of the prediction models as illustrated in Equation 5.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \overline{y}_t|}{y_t} \tag{5}$$

where y_t is the actual value of power demand, $\overline{y}_t$ is the predicted power value for the instant of prediction t and n is the total number of samples.

In this section, we have settled the underlying concepts used in our study. In the next section, we will detail the data utilized for the experiments.

III. Dataset description

In the current section, we introduce two datasets for the experiments. On the one hand, we have the data of the power demand registered every half hour (Table I). On the other hand, we have social activity data from Twitter public *API*. We detail both datasets below:

a) Country-level electric power demand: is provided by the Operations Committee of the National Interconnected System (Comité de Operaciones del Sistema Interconectado Nacional, *COES*). This private entity ensures the security of supply of electricity, allowing the population enjoyment of electricity supply in quality and enabling suitable conditions for the development of the economic activities conditions. This available public data is composed of the timestamp, the country level real consumed electric power, daily prediction and weekly forecast as it is presented in Table I.

Timestamp	Real (MW)	Daily(MW)	Weekly(MW)	Count
01/05/2016 00:30	5047.645	5103.366	5061.901	441
01/05/2016 01:00	4908.854	5001.318	5061.901	251
01/05/2016 01:30	4875.619	4901.389	4942.144	538

TABLE I. DATA EXAMPLE OF COUNTRY LEVEL ELECTRIC POWER DEMAND

The COES's prediction model, used to estimate daily and weekly electric power demand is detailed in [9].

b) Social Activity: this data was captured by the public Twitter API[1] gathering tweets originated in a bounding box covering all Perú. We obtained around two million of tweets not only from Perú but also from border areas of Ecuador and Brazil. Then, we filtered all the tweets which were not originated in Perú to finally obtain 1.778.631 tweets from April, May and June 2016. In the end, we counted the number of tweets emitted every 30 minutes as it is described in Table I in the column "*count*".

c) Training and test datasets: are generated by splitting data into two non-overlapping periods. The training dataset is composed of the half-hourly data of the last day of the month, while the test dataset contains the half-hourly data of the rest of the month. Regarding the training dataset, we generated two different training sets. One taking both weekdays as well as weekends and the other one has only weekdays. Table II summarizes the number of records per dataset per month where *Train dataset* is the training dataset including weekdays and weekends, and the *Train wd dataset* contains only weekdays.

In the next section, we will use the data sets mentioned above for the experimentation.

[0] http://www.coes.org.pe
[1] https://dev.twitter.com/

Month	Train dataset	Train wd dataset	Count
April	1392	960	48
May	1440	1008	48
Jun	1392	1008	48

TABLE II. DATA EXAMPLE OF TWITTER

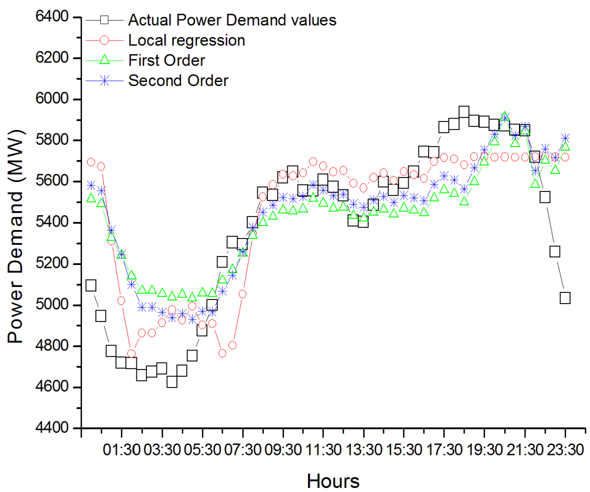

Fig. 1. The actual and the estimated power demand in Perú for May 31^{st} vs the hours of the day using Regression models

IV. EXPERIMENTS AND RESULTS

In the present section, we detail how experiments were conducted (methodology) and we show the obtained results. The method used to estimate electricity power demand by social activity data consists of three steps. The first step is to verify if there exist a correlation between historical power electricity demand and the volume of tweets. Accordingly, we compute the Pearson correlation between these datasets obtaining positive correlation values of 0.7, 0.7 and 0.6 for April, May, and June, respectively. These results confirm our intuition about the relation of human activity captured by social networks (*e.g.,* Twitter) and power demand. In the second step, we have tested three different regression models: Linear, Polynomial and Local regression (*c.f.*, Subsection II-A) to estimate country-level power electricity demand. We use the training set of each month (April, May, and June) to predict its last day. Using the training dataset for the month of May, we obtain the curve illustrated in Figure 1. The last step was to measure the MAPE for finding the most accurate predictor based on regression models. Thus, we computed the MAPE between the real historical data and the three different regression models. Results are summarized in Figure 3, where we can observe that Local regression (3.73%-6.23%) is more accurate than the Linear (3.87%-7.89%) and the Polynomial (3.70%-7.29%) regressions.

The methodology used in this work for the neural network is detailed below. First, the data is separated in training and testing datasets. For the training, set historical data for every day of April, May and June were taken. Thus, they have developed three neural networks for the three months.

Once the three neural networks adjusted their settings, they were applied to the test dataset, which was the last day of each month (it is clear that the data considered in the testing step were not considered in the training set). For the performance of the neural network in the forecast, we compute the MAPE value described in Equation 5.

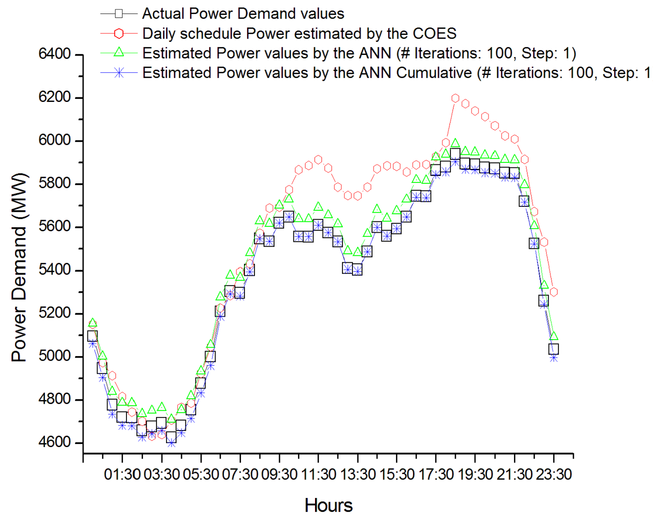

Fig. 2. The actual and the daily schedule power demand estimated in Perú as well as the estimated power values by the ANN and the ANN cumulative vs the hours of May 31^{st}.

A Multi-layer Perceptron *MPL* neural network was used. Learning is carried out through backpropagation. In this paper, the ANN was trained to estimate a step forward, for example, it used the energy demand data at time t, to estimate the state $t + 1$, in this way, the neural network was used to estimate time series.

The difference between the ANN and the ANN with cumulative training is that the last one consider not only the current training window data but also all the data, from the beginning up to the end.

Figure 2 shows the actual and the daily schedule power demand estimated in Perú as well as the estimated power values by the ANN and the ANN with cumulative training vs the hours of May 31^{st}.

In this work, the MAPE value for the last day of May, using the ANN with cumulative training, was equal to 0.34; which is an excellent value. Besides it considerably improves the prediction of power demand compared with the estimated daily schedule by COES. That means that the pattern of power demand is very well determined by the predictor (ANN with cumulative training).

In this section, we have presented our findings. The next section concludes the study and presents some future research directions.

V. CONCLUSION

In the current work, we have presented two different methods to predict country-level power demand using social activity captured by regression models and historical consumption patterns provided by the *COES*.

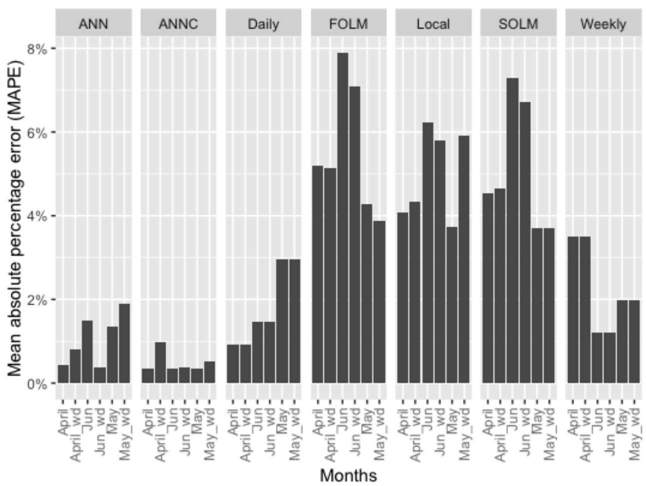

Fig. 3. MAPE of the Artificial Neural Network (ANN), ANN cumulative (ANNC), Daily predicted (Daily), Linear model (FOLM), Second order (SOLM) and Local regression (Local) and Weekly predicted (Weekly) models *vs.* real power demand.

Despite that, the power consumption is related to more devices which are not connected to the Internet, the use of Twitter data demonstrated to be an accurate tool to predict power demand forecasting; showing the remarkable power of social media [18] [17]. Other platforms such as Facebook, Google+ or Instagram could provide similar or better results by themselves, or in combination.

Apropos the regression models, Local regression estimates the best among the other regression models obtaining a MAPE between 3.73% to 6.23%. We observe that social networks characterize human activity, which is dependent on power electricity. Accordingly, social network activity could be used to estimate country-level power demand indirectly when no historical data is available.

The ANN modeling, with cumulative training, presented in this study, was able to predict the power demand of the last days of the months, April, May and June 2016, with a MAPE of 0.34% to 0.98%. These results show a more accurate prediction than the actual forecasting method, which its MAPE is between 0.91% and 2.96%. Thus, the neural network can be used effectively for this kind of prediction. This new power demand predictor presents a high precision and low MAPE value. For future work, we are considering a longer number of days for the forecast.

It is worth noting that the trained ANN captures key aspects of the phenomenon of power consumption. Therefore, the model does not depend on conditions or rules such as working days and holidays to estimate power demand. For instance, the model was able to predict the power consumption at a country-level of the Saturday the 30^{th} of April with less than a 1% of the MAPE with both, considering the whole month and with only weekdays training sets. In the future, we plan to combine a set of ANNs for different time windows in the morning, evening and at night to improve prediction.

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