A CLUSTERING NEURAL NETWORK MODEL APPLIED TO ELECTRICITY PRICE RANGE FORECAST

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Abstract – With electricity markets birth, electricity price volatility becomes one of the major concerns for their participants and in particular, for the producers. Whether or not to hedge, what type of portfolio is adequate, and how to manage that portfolio are important considerations for electricity market agents. To achieve that, load and electricity price forecast have a high importance. This paper provides an approach applied to price range forecast. Making use of artificial neural networks (ANN), the methodology presented here has as main concern finding the maximum and the minimum System Marginal Price (SMP) for a specific programming period, with a certain confidence level. To train the neural networks, probabilistic information from past years is used. To increase accuracy and turning ANN training more efficient, a K-Means clustering method is previously applied. Results from real data are presented and discussed in detail.

Keywords: Price Forecast, Risk Management, Clustering, Electricity Markets, Confidence Level.

I. INTRODUCTION

Until the eighties, the model traditionally used in most countries is based on monolithic regulated public utilities, where the prices were stable and predictable over a relatively long time horizon and, therefore, the risks involved in the energy business were very low. However, this changed dramatically. The liberalization of the electric sector, beside the price volatility introduction, leads to a clear competition on several activity sectors and in particular on the production sector. Power producers have now to change the way they do their business and to evolve from monopolist to unbundled companies in direct competition [1, 2].

A clear sign of these changes has been the creation of several energy exchanges across the world. These exchanges have a similar structure when compared to traditional commodities exchanges.

In electricity markets we find products for physical delivery, namely spot contracts established on hour or half-hour basis and forward contracts. To increase liquidity and allow market agents to practice the hedge, futures and options contracts were introduced in electricity markets.

The most important feature that distinguishes electricity markets from commodities markets is the non-storability of the electricity. It is impossible to storage large quantities of energy today and fulfill contracts to delivery that energy tomorrow. The non-storability causes significant wide movements in spot prices that associated to heat or cold waves, can lead the spot price to climb up to 1000% for short periods of time [3]. This is unusually high even when compared with commodities markets. Another implication of the non-storability of electricity is the impossibility to transfer a certain amount of energy from one part of the world to another or even from a neighboring region without considering the transmission constraints. These difficulties, besides the influence of fuel prices [4] and weather conditions, introduce special characteristics to electricity prices and, in particular, to the spot price. Characteristics such as: high volatility, price spikes and mean-reversion are now specific characteristics of prices in liberalized electricity markets. Those characteristics bring a lot of difficulties to electricity markets agents for who the risk management is at the moment more important than ever.

Some studies have been made in price forecast applied to electricity markets. In [5], artificial intelligent tools are applied to forecast spot prices, namely a combination of neural networks and fuzzy logic is used to predict prices. In fact, besides the early skepticism, neural networks have now an extensive use in load [6, 7] and in price [8] forecast. Fuzzy techniques together with neural networks are used to predict possible prices range [9, 10]. Stochastic processes are also used to analyze time series. In [11], ARIMA processes, a class of stochastic processes, were used to predict next-day electricity prices in mainland Spanish and in California markets. In [12], two forecasting tools based on dynamic regression and transfer function models are presented.

However, beside of the importance of the accuracy on price forecast, a single forecasted value is not enough for an efficient risk management [13]. Following the previous efforts by the authors in risk management [14, 15] and in price forecast [16], we present in this work a price range forecast method. The method presented here makes use of neural networks to predict the electricity price range, with a certain confidence level α, for the programming period in question. To train the neural networks, statistic information from historical data is used. To increase the accuracy and to turn the training of the neural networks more efficient, K-Means clustering method is used to partition the data.

On a summarized way, the paper is organized as follows. The introduction of the model is made in Section II. Numerical results for the mainland Spanish market are presented in Section III. In Section IV conclusions are made.

II. MODEL DESCRIPTION

Making decisions based exclusively on a single value is highly risky, unless we are 100% certain that the forecasted price will occur. With the liberalization of the electricity markets, the participants of that sector are now in direct competition, and the success of their activity depends, in great part, on the accuracy of the price forecast. However, the high volatility of the System Marginal Price (SMP) difficult that task and consequently the risk management.

The model presented in this work, aims to give answers to the price forecast problem. In fact, this work is related with a decision-support system developed by the authors, that has as objective to help the electricity market agents, and in particular the producers, to decide what type of contracts they should establish for a certain programming period, with the objective to increase the profits and simultaneously to practice the hedge against the SMP volatility [14] – [16].

The model objective is to find the expected maximum and minimum prices for the programming period in question, with a certain confidence level α. To achieve that, we use neural networks and statistical information from historical data. The historical data, used to train the neural networks, is presented in Fig. 1 and are real data from the mainland Spanish market between January 2002 and July 2003[1].

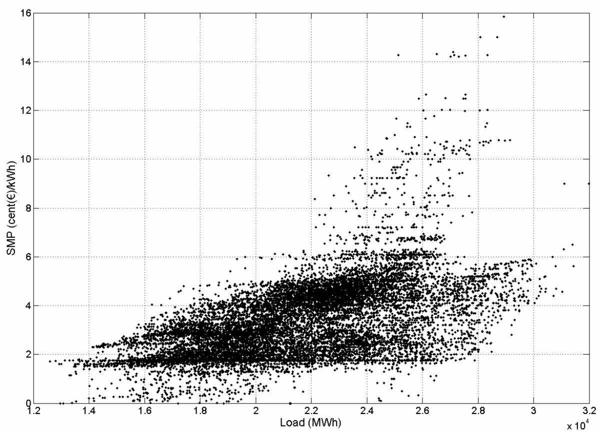

Figure 1- Load vs SMP for mainland Spanish market between January 2002 and July 2003

[1] [http://www.omel.es/frames/es/resultados/resultados_index.htm]

A. *Training and Validation Data*

To train and validate the neural networks, statistical information is needed and we get it from historical data. First, the historical data is divided according to the month of the year, the day of the week and the hour of the day. For each month of the year, day of the week and hour of the day, we divide the load on a group of equally spaced intervals L. The size of the load interval L is not fixed, varying accordingly to the month of the year, day of the week and hour of the day. Instead of fixing the interval size we fixed the number of intervals. For each load interval, and for each confidence level α, we find the percentile $\left(50+\frac{\alpha}{2}\right)$ and the percentile $\left(50-\frac{\alpha}{2}\right)$. Note that we use a bilateral confidence level instead of a unilateral one. However, a unilateral confidence level could also be applied.

Based on that information, for each historical data point, we find the month of the year, day of the week, hour of the day, the load interval that it belongs to and the price of the previous period.

Two groups of data are created, the training and the validation data group. The input vectors for the training and validation have the form $I_t = [M_t, D_t, H_t, C_t^{máx}, C_t^{min}, P_{t-1}]$, where:

- I_t represents the input vector for period t
- M_t represents the month of the year for the period t. This input belongs to the interval [1,2,…,12], with 1=January,…, and 12=December
- D_t represents the day of the week for the period t. This input belongs to the interval [1,2,…,7], with 1=Monday,… and 7=Sunday
- H_t represents the hour of the day for the period t and belongs to the interval [1,2,…,24]
- $C_t^{máx}$ represents the maximum load in the interval that the period t belongs
- C_t^{min} represents the minimum load in the interval that the period t belongs
- P_{t-1} represents the SMP of the previous period t.

The training and validation target vectors are of the form $T_t = [Pmax^{\alpha}_t, Pmin^{\alpha}_t]$, where:

- T_t represents the target vector for the period t
- $Pmax^{\alpha}_t$ represents the maximum price, with confidence level α, for the interval that the period t belongs to
- $Pmin^{\alpha}_t$ represents the minimum price, with confidence level α, for the interval that the period t belongs to

B. *Neural Networks*

The number of neural networks used to forecast the electricity price range is dependent of the number of clusters that we find in the training data. To find similarities in the training data, a K-Means clustering method was used. K-Means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves objects between clusters until the sum cannot be decreased any further. Due to the fact that we do not have previous knowledge of how many clusters are really in the data, we have to try several number of clusters and find the optimum number. A graphical representation of the neural networks used in this model is presented in Fig. 2.

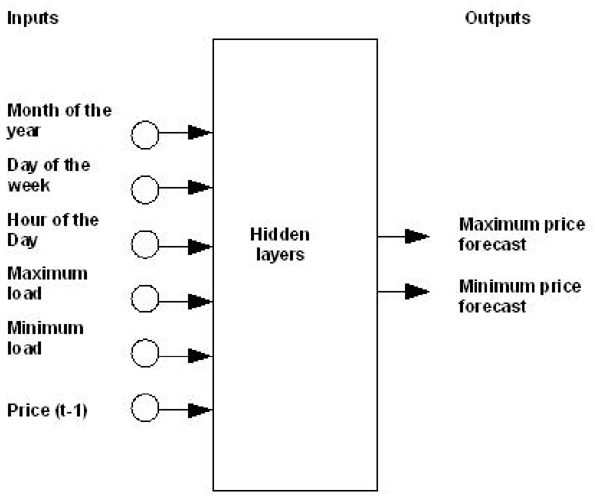

Figure 2- Graphical representation of the Artificial Neural Networks used

The training method used was Levenberg-Marquardt algorithm that is a variation of Back-propagation algorithm. Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix.

Before training, the inputs and targets were scaled so that they fall in the range [-1, 1]. However, before scaling, the load was multiplied by a factor β to avoid a high variance between input data. The neural networks outputs needs to be de-scaled to generate the desired forecasted values.

A tangent sigmoid function was chosen as the transfer function for the hidden layers, and a linear function for the output layer.

To improve generalization and reduce training time *early stopping* criteria was used. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned.

To test the model, it is necessary to find the cluster that the input vectors belong to and, consequently, the artificial neural network to use. For each test input vector, the distance to the centroid of each cluster is calculated and, by that means, found the cluster that it belong to.

III. Case Study

To test our model, we use the historical data presented in Fig. 1. For this study case, we use a confidence level α equal to 95%. Because the number of intervals is fixed, the load interval size is dependent of the month of the year, the day of the week and of hour of the day. The load interval size, in function of the month of the year, is presented in Fig. 3. Has we can see from Fig. 3, the months of the year that have higher load variance are winter months, namely the months of December and January. The month that has lower load variance is September.

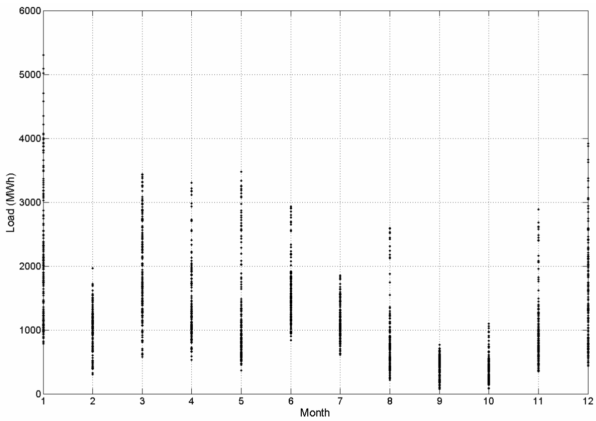

Figure 3- Load interval size in function of the month of the year

The load interval size, in function of the day of the week, is presented in Fig. 4. From this figure, we can see that Wednesday is the day of the week with higher load variance and Saturday is the day of the week with lower load variance.

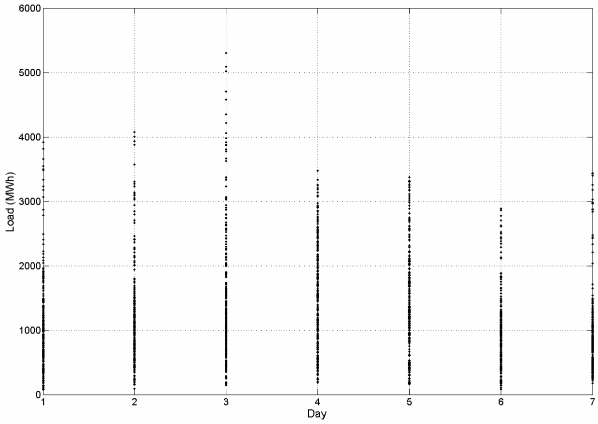

Figure 4- Load interval size in function of the day of the week

In Fig. 5, the load interval size, in function of the hour of the day, is presented. From the same figure, the hours 9 to 14 are the hours with higher variance. However, hours 14 to 22 also have a high load variance.

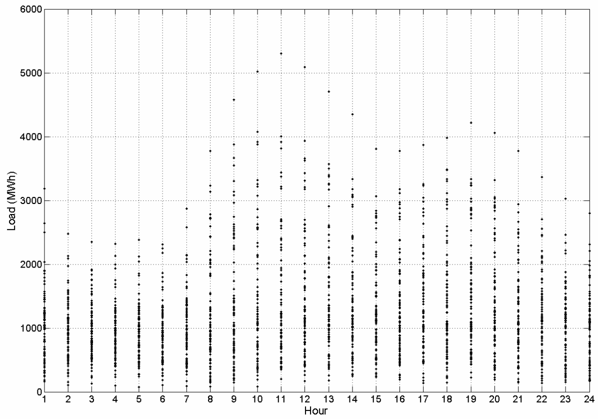

Figure 5- Load interval size in function of the hour of the day

A. Clustering and ANN Structure

The number of neural networks used is dependent of the optimum number of clusters founded for the training and validation data. To find those clusters we use the K-Means clustering method. In K-Means method we used as objective function the minimization of the square of the Euclidean distance.

After several attempts, the conclusion is that the optimum number of clusters is two.

To get an idea of how well-separated the resulting clusters are, a silhouette plot is presented in Fig. 6. This silhouette plot displays a measure of how close each point in one cluster is to points in the neighboring clusters. This measure ranges from +1, indicating points that are very distant from neighboring clusters, through 0, indicating points that are not distinctly in one cluster or another, to -1, indicating points that are probably assigned to the wrong cluster.

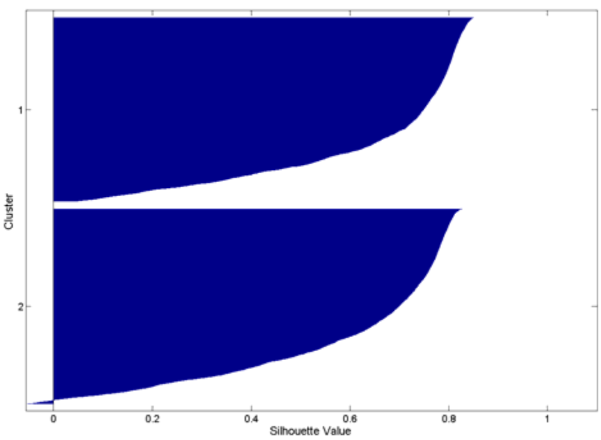

Figure 6- Silhouette plot for two clusters

The average of the silhouette values, in function of the number of clusters, is presented in Table I. From this table we can see that the mean of the silhouette values is higher for two clusters.

Table I- Average of the Silhouette Values in function of the number of clusters

Number of Clusters	Average of the Silhouette Values
2	0.6297
3	0.4760
4	0.4584
5	0.4056
6	0.3755

Because the optimum number of clusters to use is two, the model for this case study will use two neural networks, one for each cluster, and each one has the structure 6-15-15-2. That is, the neural networks have two hidden layers with fifteen neurons each and one output layer with two neurons. After several tests with different structures, this particular structure was chosen because it guarantees better results, namely, in accuracy and training time.

B. Model Test and Results

To test the model, we forecast the electricity range for the first week of August and for the first week of October of 2003. The considered confidence level α was 95%.

However, to test the model it is necessary to have the forecast load values for those weeks. The model used to forecast load values is based on artificial neural networks. To its output we applied a scale factor φ to get the maximum and the minimum load forecast for the programming period in question. The scale factor φ is half of the load interval magnitude used to train the ANN and, like we saw previously, it is a function of the month of the year, the day of the week and of the hour of the day.

The main issue at this point is to find to which cluster belong the test input data. To solve that problem, we compare the Euclidean distance from each input test data and the clusters centroid, or center. The minimum distance defines at which cluster the input test data belongs to.

The electricity price range forecast for the first week of August 2003 for the mainland Spanish market, with confidence level α=95%, is presented in Fig. 7. The real load for the same period is presented in Fig. 8.

The electricity price range forecast for the first week of October 2003 for the mainland Spanish market, with confidence level α=95%, is presented in Fig. 9. The real load for the same period is presented in Fig. 10.

Analyzing figures 7, 8, 9 and 10, we can see that the correlation between load and price is higher for the October week, especially at the weekends.

From Fig. 7 and Fig. 9, we can see that the price range forecast, with confidence level α=95%, has a high accuracy when compared with the real price.

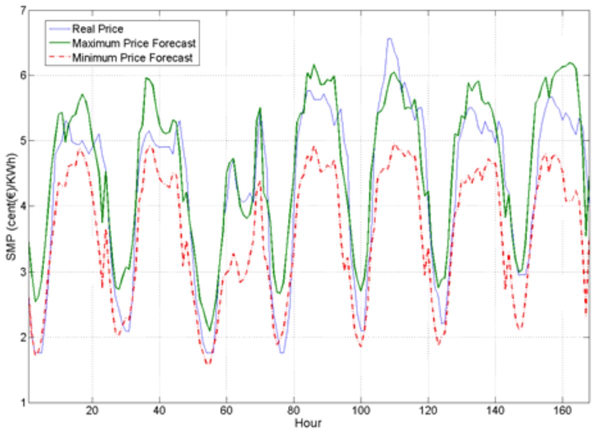

Figure 7- Electricity price range forecast for the first week of August month of the year 2003

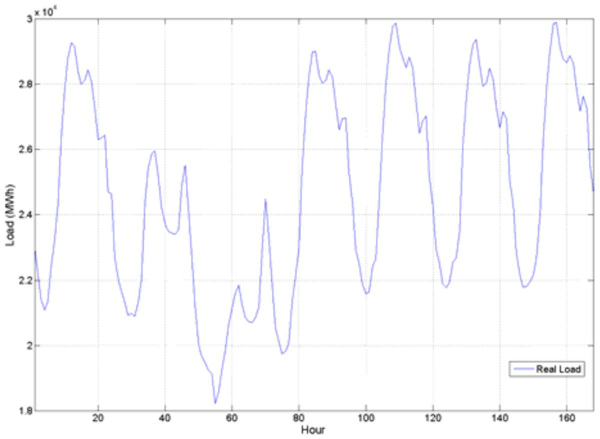

Figure 8- Real load for the first week of August month of the year 2003

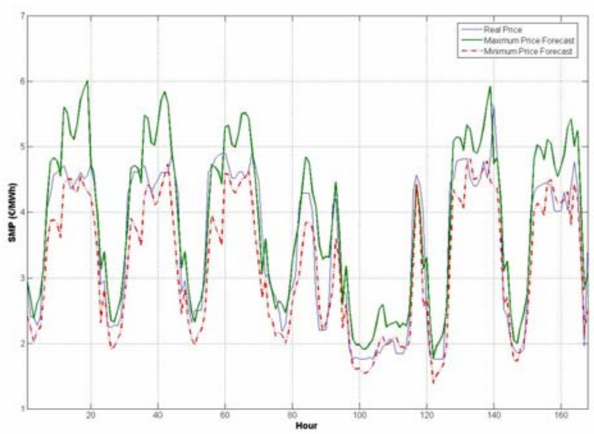

Figure 9- Electricity price range forecast for the first week of October month of the year 2003

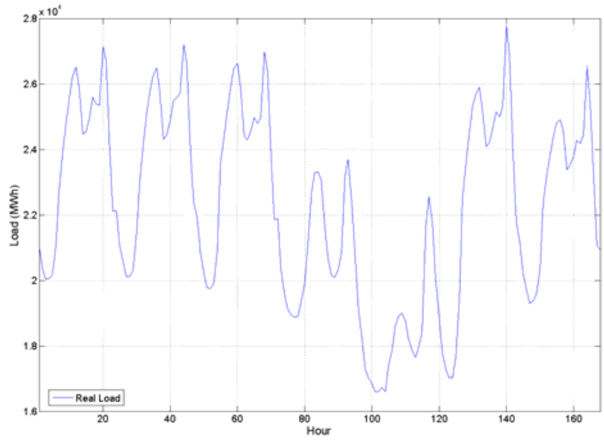

Figure 10- Real load for the first week of October month of the year 2003

Statistical information from historical data plays here an important role. To achieve good results, this methodology should be updated dynamically.

IV. Conclusions

One of the major concerns for the agents of any market, and in particular of electricity markets, is to find the optimal portfolio that maximizes the profits and simultaneously allows the practice of the hedge. To achieve that, price forecast plays here an important role. However, it is not a good practice to make contractual decisions based exclusively on a single price forecast unless, of course, the agents are one hundred percent sure of the market price value, which is very difficult to happen in real markets.

Due to specificities of the product electricity, the risk management in this type of markets is more difficult. To help the agents of the electricity markets, we present in this paper a model that allows finding a range for the SMP, with a certain confidence level, based on historical statistical data information, making use of clustering techniques and artificial neural networks.

We do not make any statistical assumption about the electricity price distribution, which is an important advantage of this approach. In this model, neural networks assimilate statistical information from historical data and apply them to new periods in the future.

The patterns reveled by electricity prices turn more difficult the statistical information assimilation by the ANN. To solve this problem, clustering techniques are used, namely the K-Means clustering method. Clustering techniques enable to investigate whether a group structure exists and use each group to train only one neural network. This allows that each neural network learns in a more efficient way the information carrying by the historical data.

In this paper we presented results for only one confidence level. However, this model has already been tested with other confidence levels and results were also very good.

The model here presented reveals to be very useful in risk management and produces good results in finding a range with scientific accuracy for SMP in mainland Spanish market.

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